Development of a System-Dynamics-based Methodology for Comprehensive Community Energy Planning

Bilal Bugaje

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“Citations?

Not yet.

First principles first”

- Hikima

Abstract

Global trends are leading to a rise in Energy Planning (EP) at the community-level, and Distributed Energy Resources at the residential-level, while seeking a more sustainable future; EP involves decision-making about energy systems. Whilst Community Energy Planning (CEP) aims to be holistic and participatory, it comprises multiple disjointed methods that lead to two challenges. The first challenge is hindrance to a holistic approach and understanding of the energy system, while the second challenge is hindrance to participation from diverse stakeholders. However, System Dynamics (SD), which is a methodology for mental and simulation models, looks promising as a basis for a comprehensive CEP methodology that would lead to a more holistic and participatory CEP.

Consequently, the research question of the thesis is: is a System Dynamics approach an effective and comprehensive methodology for sustainable Community Energy Planning? The research aims were broken down into specific objectives which are addressed in specific chapters. The objectives that required creating simulation models were addressed as case-study chapters, and arranged such that later chapters build on models created in earlier chapters, culminating in the combination of multiple earlier models.

Drawing on the literature of Sustainability Assessment (SA) and the methods used in CEP, it is argued that CEP is a form of SA because it utilises Sustainability Indicators to appraise models of planned energy systems. Furthermore, a comprehensive CEP methodology is proposed that is centred around SD, which addresses some of the challenges of CEP. Subsequently, gaps were identified in the demonstration of SD among the methods of the proposed CEP methodology, which was found to be in the area of bottom-up simulation models. The case-study chapters are the first attempts in the following, while utilising SD from the bottom-up: a valid supply-side model; use of the supply-side model in decision-making analyses; a valid demand-side model; use of the demand-side model in decision-making analyses; and combination of supply-side models, and with a demand-side model. Additionally, there are other significant contributions from the case-studies. In conclusion, it is argued that SD could be an effective basis for a more comprehensive CEP methodology, and that this research can be considered a step towards that aim.

Outputs from Research

The following are the some of the outputs from the research in terms of presentations at conferences, awards, and papers published in conference proceedings and journals.

Presentations

- Paper presentation: Bugaje, B. (2019) ‘A Bottom-Up Supply-Side Simulation Model of Residential and Community Energy Systems using System Dynamics’, in *Manchester Energy and Electrical Power Systems (MEEPS) Workshop 2019*. Manchester, UK.
- Poster presentation: Bugaje, B. (2020) ‘Residential Energy Consumption: An End-Use Simulation Model’, in *UK System Dynamics Conference 2020*. Online. Available at: https://www.youtube.com/watch?v=rpLu4lH1qkA.
- Paper presentation: Bugaje, B., Rutherford, P. and Clifford, M. (2021a) ‘A Bottom-up Supply-side Simulation Model of Residential and Community Energy Systems using System Dynamics’, in Fakhimi, M., Robertson, D., and Boness, T. (eds) *Proceedings of the Operational Research Society Simulation Workshop 2021 (SW21),* pp. 315–324. doi: 10.36819/SW21.03.
- Paper presentation: Bugaje, B. (2021) ‘Simulating Bottom-up Supply-Side Residential Energy Systems with Non-linear Conversion Efficiency’, in *UK System Dynamics Conference 2021*. Online. Available at: https://www.youtube.com/watch?v=OtptOax4pbQ.
- Paper presentation: ‘A Comprehensive Language for Modelling in Energy Planning’, at The Earl of Wessex Future Energy Conference 2021. London, 15th November, 2021.

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- Bugaje, B., Rutherford, P. and Clifford, M. (2021b) 'A systems dynamics approach to the bottom-up simulation of residential appliance load', *Energy & Buildings*. Elsevier B.V., 247, p. 111164. doi: 10.1016/j.enbuild.2021.111164.
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List of Acronyms

ABM	-	Agent Based Modelling
AD	-	Architecture Design
AHP	-	Analytic Hierarchy Process
AMDLP	-	Annual Mean Daily Load Profile
AT	-	Appropriate Technology
CEP	-	Community Energy Planning
CES	-	Community Energy System
CI	-	Composite Indicator
CLD	-	Causal Loop Diagram
CM	-	Community Microgrids
CMP	-	Community Master Plan
CRP	-	Community Regulatory Plan
CSP	-	Community Site Plan
DC	-	Direct Current
DDP	-	Delay Duration Profile
DER	-	Distributed Energy Resource
DR	-	Demand Response
DRSA	-	Dominance-based Rough Set Approach
DSM	-	Demand-Side Management
DSO	-	Distribution System Operator
DTP	-	Delay Time Profile
EAC	-	Equivalent Annual Cost
EIA	-	Environmental Impact Assessment
ELECTRE	-	Elimination Et Choix Traduisant la Realité
ELR	-	Energy Loss Ratio
EMAS	-	Eco-Management and Audit Scheme
EMS	-	Energy Management System
EP	-	Energy Planning
ES	-	Energy Storage
FMEA	-	Failure Mode and Effect Analysis
GEP	-	Generation Expansion Planning

GMB	-	Group Model Building
GUI	-	Graphical User Interface
HDI	-	Human Development Index
HLDC	-	Hourly Load Duration Curve
HVAC	-	Heating, Ventilation and Air Conditioning
IA	-	Integrated Assessment
ICES	-	Integrated Community Energy System
IDE	-	Integrated Development Environments
IEP	-	Integrated Energy Planning
LCA	-	Life Cycle Assessment
LCA	-	Lifecycle Analyses
LP	-	Linear Programming
MADM	-	Multi-Attribute Decision Making MADM
MAUT	-	Multi-Attribute Utility Theory
MBC	-	Model Boundary Chart
MCDA	-	Multiple Criteria Decision Analysis
MDM	-	Meadows Data Manager
MILP	-	Mixed-Integer Linear Programming
MM	-	Mediated Modelling
MODM	-	Multi-Objectives Decision Making
NAIADE	-	Novel Approach to Imprecise Assessment and Decision Environments
NPV	-	Net Present Value
OR	-	Operational Research
PANDA	-	Participatory Appraisal of Needs and the Development of Action
PBP	-	Payback Period
PCG	-	Prosumer Community Groups
PROMETHEE	-	Preference Ranking Organisation METHod for Enrichment Evaluation
PSM	-	Problem Structuring Methods
RES	-	Residential Energy Systems

RTIP	-	Real-Time Integration Platform
SA	-	Sustainability Assessment
SAM	-	System Advisor Model
SCR	-	Self-Consumption Rate
SD	-	System Dynamics
SDG	-	Sustainable Development Goals
SEG	-	Smart Export Guarantee
SFD	-	Stock and Flow Diagram
SI	-	Sustainability Indicators
SOSM	-	System of Systems Methodology
STEP	-	Social Technological Economic and Political Factors
SSDM	-	Soft System Dynamics Methodology
SSM	-	Soft Systems Methodology
SSR	-	Self-Sufficiency Rate
TA	-	Technology Assessment
TBL	-	Tripple Bottom Line
TOPSIS	-	Technique of Order Preference by Similarity to Ideal Solution
TUD	-	Time-Use Data
TUS	-	Time-Use Survey
UNFCCC	-	United Nations Framework Convention on Climate Change
VFT	-	Value Focused Thinking
VPP	-	Virtual Power Plant
WEC	-	With Energy Conversion
WOEC	-	Without Energy Conversion

Preface

I would like to use this section to highlight the importance of culture to technology solutions, and the potential of the System Dynamics (SD) methodology to reflect cultural peculiarities in modelling for energy solutions. Whilst the body of the thesis does not directly address culture, the outcome of the research could lead to more culture-sensitive technology solutions in the future. That is my hope.

How does culture undermine energy technology as a solution to a problem? Can cultural factors be modelled in planning energy solutions? These were the questions that stimulated the journey which led to the research presented in this thesis. Culture refers to the way people do things and the meanings of what they do [1] as in the phrase 'work culture', and cultural factors include attitudes, norms, values and beliefs. Living in a low-income country, Nigeria in particular (what follows is largely informed by the experience of the author in Nigeria and may not reflect other low-income countries), it was clear from the onset that technology does not necessarily equal solution. If so, then why do technologies that are acclaimed and have been demonstrated to be effective in some parts of the world fail when transferred to other locations?

Often, the direction of technology transfer is from institutions of high-income countries to low-income countries [2]. These institutions tend to project their agenda, framed as “relevant, and even necessary” while casually recommending “departure from tradition” in the culture of the recipients [2]. Historically, technology transfer has been instrumental in colonisation, and has contributed to the underdevelopment of the colonies with enduring effects [3]–[6]. Today, technology transfer perpetuates neo-colonialism which utilises colonial structures and relationships to control low-income countries. The first United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol, which are foundational in deciding the global sustainability agenda, require transfer of environmentally sound technologies [7], [8], but cultural appropriateness is not a requirement. High-income countries, their institutions, and the institutions they control decide what it means to be environmentally sound, then they expect the low-income countries to conform to their ‘superior’ knowledge in their ‘civilising mission’. Some have called for adaptation of the transferred technology [9], but it is not clear if this includes cultural factors.

Sometimes, the technology has been demonstrated in another low-income country with a similar physical climate, yet the technology may not be a solution in another transferred location, which indicates that cultural preferences may be a factor in the explanation. The effect of culture can be seen in [10] where an increase in income did not lead to more efficient and cleaner cooking energy as expected from the perspective of the decision-makers in high-income countries, as in [11], instead a mix of energy is used, and higher income led to wider energy options; after all, some foods are culturally cooked with particular fuel. Furthermore, households with children willingly use increased and more expensive electricity due to their cultural preference of having ‘quality family time’ [12]. It has also been argued that the failure of adoption of efficient stoves, despite interventions for over three decades, is due to disregard for cultural preference of the users of the technology [2]. There are other anecdotes on cooking technology that suggest the effect of culture, for example, where efficient stoves were culturally more appropriate as furniture and status symbols, than as stoves. Ultimately, the cheapest and most efficient technology may not be a solution if it is not used as intended, or even used at all; cultural preferences can be a major barrier to the success of a technology.

Some of the barriers to the development of transferred sustainable energy technology in Nigeria include: poor maintenance culture [13]; poor project management [14], [15]; lack of awareness on energy consumption [14], [15]; and poor land use [14], [15]. These barriers are culturally determined in so far as the attitudes of the people involved are influenced by their culture. Generally, cultural considerations are missing in recommendations for successful implementation of transferred sustainable energy, for example in [9], [13]–[20]. When cultural considerations are missing in technology transfer, the presumption that the culture of a high-income country (technology’s origin) is the same as that of a low-income country (technology’s destination) without consideration signifies the neo-colonial hegemonic dynamic; which may be patronising, or an oversight at best.

Since the problems being addressed by the technology persist regardless of blame or intention, why not accommodate the cultural peculiarities of the low-income countries in the design, implementation and use of the technologies, instead of expending resources trying to get low-income countries to fit to a standard that is imposed? The aim of any good design is to enable the user of the system to use it as intended with minimum cognitive load [21]. Those imposed on suffer from ‘double consciousness’ [22] which has been shown to increase cognitive load significantly [23], notwithstanding the ethical implication of inducing double consciousness. Standardisation, which is to impose on a user 'arbitrary mappings and difficulties', is a last resort, and considered the absence of design [21]. The long-term solution to the divergence in cultural meanings is to organically generate and negotiate meanings rooted in the value system and worldview of the low-income population, not as a neo-colonial imposition. One way to accommodate the cultural peculiarities would be to include the perspectives of the users in the design, implementation or use of the technology.

Accordingly, the following research areas were explored: Appropriate Technology (AT), policy documents; Technology Assessment (TA); Sustainability Assessment (SA); and Multiple Criteria Decision Analysis (MCDA). They were found to be culturally insensitive with a few exceptions in TA, SA and MCDA. SD was identified as a recurring methodology which is utilised in the application of all three, especially with regard to modelling soft variables that are open to interpretation (cultural factors are soft variables). For example, to make TA culturally sensitive and quantitative, a framework was proposed and demonstrated based on SD [24]–[27]. Furthermore, SD was used for SA in [26]–[29], and as a Problem Structuring Method (PSM) in [30]–[35] which is combined with MCDA to avoid solving the 'wrong problem' [30]. Additionally, SD was used to assess and strengthen policy coherence across multiple sectors (including energy) within the context of the Sustainable Development Goals (SDG) [36]–[41]. Therefore, SD has the promising potential to incorporate cultural variables and unify all the explored research areas.

1 Introduction

1.1 Research Motivation

The motivation to explore energy planning and development came from the author's religious values, especially justice and betterment across human and non-human communities. Therefore, sustainability, as an ideal, became a starting point of this research because of its global currency, concern for non-human communities, and potential to accommodate cultural peculiarities. The research in this PhD thesis focuses on human communities. Thus, the Human Development Index (HDI) is a logical next step. HDI, which combines indicators of sustainability [42], measures the three dimensions of long healthy life, education and standard of living [43]. Furthermore, HDI is correlated with equitable access to energy [44], [45].

Whilst there has been a steady decrease in the number of people without access to electricity since 2013, the progress reversed in 2020 due to the COVID-19 pandemic [46]. As at 2019, 770 million people (10% of the world population) did not have access to electricity [46]; where access does not account for affordability [47]. Most of the countries with medium and low HDI in the 2020 Human Development Report [42] are the countries with low access to energy [46], [47], with about 10-fold and 100-fold variability in energy and electricity consumption respectively, across the world [47]. There are ongoing efforts to address the energy access gap, which include research in energy technology and energy development [48]. Energy development is achieved via Energy Planning (EP) which is the focus of this thesis.

The aim of EP is decision-making on energy-related problems, which often requires modelling energy systems. EP literature contains multiple research areas like Generation Expansion Planning (GEP) [49], [50]; Integrated Energy Planning (IEP) [51]–[53]; and Community Energy Planning (CEP) [53], [54]. CEP was selected as the area of focus because a community can be small and manageable for research but large enough to explore dynamics resulting from complexity of the system. Furthermore, CEP reflects the idea of local solutions to global problems which is promoted in the sustainability movement (as articulated in the Cancun Agreement). Moreover, CEP is likely to play a significant role in the future because the following trends are increasing its adoption [52], [55], [56]: increasing electrification; rising Distributed Energy Resource (DER); towards a carbon-neutral energy mix; changing utility business models; increasing customer engagement, self-sufficiency and sustainability of energy projects; and the rise of the prosumers (who are simultaneously consumers and producers of energy).

There are four phases in CEP [51], each with distinct groups of methods. The multitude of methods utilised in CEP makes the process disjointed, and comes with at least two challenges to the aims of CEP: hindrance to the holistic approach and holistic understanding of the resulting system, and also hindrance to the participatory approach. A survey of the possible methods to be used in CEP led to the identification of System Dynamics (SD) as a versatile methodology, with applications of SD found in methods of Phase I, Phase II and Phase III of CEP. In Phase I, SD has been used to solicit preferences of stakeholders [31], while SD has been used in Phase III to prioritise options for decision-making [35][57]–[59].

However, applications of SD in Phase II are partial, because there are demonstrations of SD in social and economic systems/models [60]–[65] (known as top-down models [66]), but no demonstrations of SD in engineering systems/models (known as bottom-up models [66]). Researchers and practitioners of CEP models are largely inclined towards engineering models, into which parameters that reflect socio-economic status and assumed cultural preferences can be input as exogenous variables, or from which impact (social, economic, ecological) can be assessed using output from the engineering system. It may be possible to input cultural perspectives, and endogenously integrate social, economic and engineering models as a holistic system if the methodological gap of SD simulation for engineering models is addressed. Therefore, this thesis does not focus on the cultural and socio-economic variables that were highlighted in the preface because such top-down applications have already been demonstrated. Instead, it focuses on addressing the gap of demonstrating SD in bottom-up models as a step towards an integrated methodology for CEP.

Consequently, SD could contribute to a comprehensive CEP methodology that addresses the two challenges above by: integrating the different methods in CEP, and providing a common accessible language for wide participation by stakeholders from different backgrounds. Having a single language to understand several methods in CEP, compared to learning a different tool for each method in CEP, encourages multi- or trans-disciplinary approaches. The details of the phases, methods and relation to SD are explored in Chapter 2.

Therefore, the motivation of this thesis is to demonstrate the application of SD in bottom-up simulation models within CEP, because SD has the potential to provide a comprehensive and accessible language for modelling in EP, and could lead to comprehensive understanding of energy systems and EP.

1.2 SD: Systems Methodology and Problems

Some background on SD will be discussed briefly, situating it within the larger discipline of Systems Methodologies, also known as Systems Thinking mainly based on [34]. The range of problems SD can handle will also be emphasised. Systems Thinking has been traced in history all the way back to Plato and Aristotle in ancient Greece whose influence may be the source of its presence in later European thinkers, but it became a discipline between the 1940s and 1960s with origins in a variety of disciplines like Management and Organisation Theory, Biology, Sociology, Control Engineering and Cybernetics. Systems Thinking was in a phase of 'normal science' [67] until the 1970s, then internal criticism led to the emergence of different methodologies and tendencies like Soft Systems Thinking, Organisational Cybernetics, Critical Systems Thinking, System Dynamics, The Fifth Discipline, and Chaos and Complexity Theory.

Systems Thinking is more intuitive than reductionist approaches from natural science. Systems Thinking emerged as a reaction to limitations of the traditional natural scientific method, which is reductionist, by approaching problems holistically. Real world problems are complex and comprise richly interconnected parts that exhibit 'emergent' properties which cannot be understood by looking at the parts individually (as in a reductionist approach). The focus then moved from the parts to the relationship between the parts, which is the system's structure. Since real world problems are difficult to replicate in terms of initial conditions, emphasis is placed on models rather than laboratory experiments, and these models capture system structures.

The various paradigms of Systems methodologies, whilst different, share language and concepts, for example: elements, boundaries, feedback, hierarchy of systems, communication, adaptation and emergence [34], [68], [69]. Systems methodologies have been classified by paradigms of social theory as functionalist, interpretive, emancipatory, and postmodern. The Systems methodologies under each are shown in Table 1; Hard Systems Thinking includes Operational Research (OR) and Systems Engineering, and MCDA is part of OR. Chapter 2 explores methodologies that fall within the interpretive and functionalist categories. The functionalist aspect of SD is discussed in more detail in Chapter 3. SD combines the advantages of Soft OR and (Hard) OR [70], which enables it to be used for mental models and simulation models respectively.

Interpretive	Functionalist	Emancipatory	Postmodern
Soft Systems Methodology; Soft System Dynamics; Interactive Management; Strategic Assumption; Surfacing and Testing; Social Systems Design; Soft Systems Thinking; Soft Operations Research; Soft Cybernetics.	Hard Systems Thinking; System Dynamics; Organisational Cybernetics; Living Systems Theory; Complexity Theory.	Critical Systems Thinking; Critical OR/MS; Community OR; Interpretive Systemology; Critical Pedagogy; Team Syntegrity.	PANDA; Knowledge Systems; Diagnostics; Generative Conversation; Systems Story.

Table 1 – Systems Methodologies classified based on paradigms of social theory

To appreciate the comprehensiveness of SD as a methodology, the grid of problem context from [34] can be used, as illustrated in Figure 1, based on [34], [71]. The grid of problem context is a two-dimensional grid used to visualise a classification of Systems methodologies according to their assumptions of problem situation; the classification is called System of Systems Methodology (SOSM). The first dimension is complexity, while the second dimension is relationship among participants. The dimensions are actually spectrums but are labelled to denote 'ideal types' [34]. Simple on the first dimension assumes "that it is easy to establish objectives for the system of concern and that it is possible to model it mathematically" [34]. Based on Figure 1, SD can be utilised for simple and complex problems with unitary and pluralist participant relationships. This grid of problem context is used to visualise the gap in SD in Chapter 2. Having situated SD as a systems methodology, the next section discusses the research question and strategy following from the research motivation in the previous section.

Participants

Complexity	Unitary	Pluralist	Coercive
Simple	System Dynamics		-
Complex			-

Figure 1 – Locating SD within the grid of problem context

1.3 Research Question and Strategy

The main research question is:

Is a System Dynamics approach an effective and comprehensive methodology for sustainable Community Energy Planning?

Given the challenges to the holistic and participatory approach of CEP that SD aims to resolve, comprehensiveness in the research question has two aspects: ability to integrate the CEP methods, and sufficiency of SD across the CEP methods. Similarly, there are two components to being effective in the case of models; to be valid and to be useful for its purpose. The purpose of a model in EP is to aid in decision-making, while validity is a minimum requirement for a model to be used [72]–[75]. Validity in SD is discussed in Chapter 3.

To manage the risk of 'failure' on a single case-study, and to address the research question, milestones have been set as objectives which are pursued in case-studies that can each stand alone. The idea is to build and explore small functional systems at the residential level which can demonstrate analyses used in EP, then eventually combine the residential systems as subsystems of a community system. After all, bottom-up simulation models are built from constituent parts [66], and system hierarchy is a fundamental feature of any systems methodology where a system is made of subsystems and so on [34], [68], [69]. Therefore, the strategy proposed is taking a bottom-up and systems approach to the design of the research project, by modelling residential systems that culminate in a community system.

On the supply-side, Residential Energy Systems (RES) can be prosumer residences that can serve as sources of Distributed Energy Resources (DER) [55]. There are many options for community-level integration of DERs with varying goals [52] which include: Community Microgrids (CM); Prosumer Community Groups (PCG); Virtual Power Plants (VPP); Community Energy Systems (CES); and Integrated Community Energy Systems (ICES). CM are perhaps the most popular of the options, and PCG was designed to address inflexibility of expansion in CM and VPP by adding new members [52]. ICES encompasses all the other integration options, and each option is an ICES if it is open to other options in the future because flexibility is at the heart of ICES [52], [53].

ICES has been defined as "a multi-faceted approach for supplying a local community with its energy requirements from high-efficiency cogeneration or trigeneration energy sources and from renewable energy technologies, coupled with innovative energy storage solutions, including the EV and energy efficiency demand-side measures" [53]. Therefore, ICES includes supply-side, storage and demand-side technologies, whereas community microgrids include only supply-side and storage technologies. To implement ICES, CEP is required, and the subsystems of an ICES can be RES.

Whilst the author had access to projects as potential case-studies in Nigeria and the UK, all case-studies are situated in the UK, due to the outcome risk assessment carried out on data collection for the potential case-studies in both countries. The potential case-studies in Nigeria were considered high-risk due to physical insecurity at the locations of the projects. Another risk was that email communication with the project teams in Nigeria was slow, in the few cases there were responses. Therefore, projects and data based in the UK were selected because they were evaluated as lower risk, and they are sufficient to make the case of the thesis.

1.4 Research Aims, Objectives and Contributions

To address the research question – in light of existing literature – the aim of this research is to demonstrate the application of SD bottom-up models in decision-making for sustainable CEP, towards a comprehensive SD-based methodology for CEP. This is because prior to this research, no work had implemented bottom-up SD, and no work had proposed a SD-based methodology that aims to integrate top-down and bottom-up models; especially in EP.

The objectives of this research are to:

1. Present SD as a versatile methodology capable of being the basis for a comprehensive CEP methodology.
2. Explore Sustainability Assessment (SA) for CEP.
3. Explore the methodologies and tools used for methods in CEP.
4. Propose a comprehensive methodology for CEP in terms of methods, that is centred around SD, and maximises integration and synergy among the constituent methods.
5. Identify gaps in the literature that demonstrate SD in the constituent methods.
6. Demonstrate the application of SD in the identified gaps using case-studies.
7. Reflect on the application of SD in the case-studies.

The methods to achieve the objectives are explained briefly in corresponding order below:

1. Introduce SD and show the various types of problems it can, and has been used to, address.

2. Conduct a literature review of SA, and show how it relates to CEP.
3. Conduct a literature review of methodologies and tools used in CEP methods.
4. Construct a comprehensive methodology by utilising SD in as many CEP methods as SD can handle.
5. Review the applications of SD in the CEP methods; while reviewing CEP methodologies.
6. Demonstrate SD in the identified gap using case-studies that:
    a. Develop a valid simulation model of a supply-side RES from the bottom-up using SD.
    b. Demonstrate an application of the supply-side SD model in decision-making.
    c. Develop a valid simulation model of a demand-side RES from the bottom-up using SD.
    d. Demonstrate an application of the demand-side model in decision-making.
    e. Integrate the supply-side and demand-side RES models, and demonstrate decision-making at community-level.
7. Identify and discuss strengths, limitations and insights from creating and application of the SD models.

Given the aims and objectives of the research, there are two main contributions of the thesis, which are related and listed below. The second contribution is actually a group of contributions, and the breakdown is also provided. These contributions are discussed in more detail in Chapter 9.

1. The proposal of a SD-centred methodology for CEP that is comprehensive by utilising SD for as many methods in CEP as possible (Chapter 2).
2. The demonstration of SD in simulation methods from the proposed methodology that have not yet been demonstrated in the literature. The SD simulation case-studies that will be demonstrated in the thesis represent the first attempts in each, and they include:
    a. A valid supply-side simulation model from the bottom-up (Chapter 4)
    b. Decision-making analyses using the supply-side model (Chapter 5)
    c. A valid demand-side simulation model from the bottom-up (Chapter 6)
    d. Decision-making analyses using the demand-side model (Chapter 7)
    e. Integration and aggregation of the supply-side and demand-side models (Chapter 8)

While demonstrating SD in the main contributions, other significant contributions were made which include:

1. A framework for designing and describing sustainability assessment studies that are based on simulation models (Chapter 3)
2. A three-dimensional classification framework for energy modelling software (Chapter 2)
3. Simulating non-linear efficiency of inverters (Chapter 4 and Chapter 5)
4. Estimating future performance of energy systems based on the behaviour of the performance indicators (Chapter 5)
5. Novel indicators for evaluating performance of energy systems (Chapter 5, Chapter 7 and Chapter 8)
6. A method of generating realistic synthetic residential appliance load (Chapter 6).

1.5 Structure of Thesis

The flow and relationship among the chapters of the thesis are illustrated in Figure 2. The first three chapters (black) are the introductory chapters, the next five chapters (red) are the case-study chapters, and the final two chapters (green) are the concluding chapters. The arrows show how a that chapter builds on previous chapters, and all the chapters that the latter build on. The content of the chapters shall be discussed.

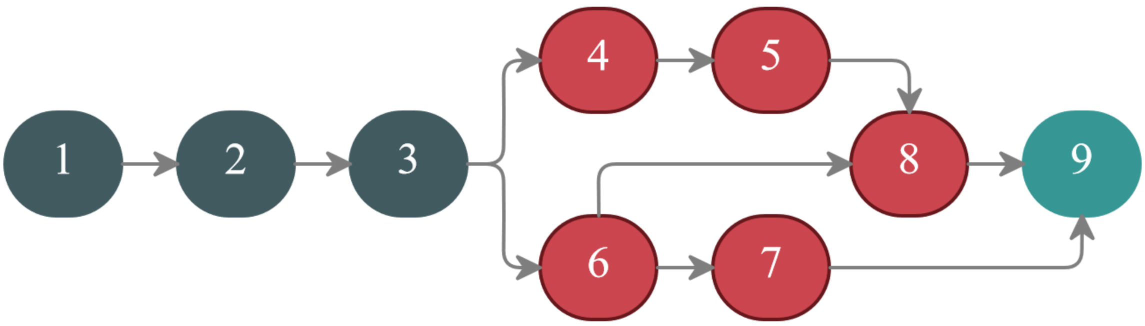

Figure 2 – Structure of the thesis showing chapters and their relationships

Literature on Sustainability Assessment (SA) and Community Energy Planning (CEP) is reviewed in Chapter 2 with focus on processes and methodologies. It will be shown that CEP can be understood as SA for energy systems. Furthermore, a SD-centred methodology is proposed for CEP to minimise the number of methodologies and maximise synergy and integration between methods in different phases of CEP. Finally, the gap in demonstration of

SD from the proposed CEP methodology is identified, and that sets the aims for the case-studies to be explored in coming chapters.

Each case-study chapter is designed to address a thesis objective, and later chapters build on some earlier ones. The progressive relationship of the chapters reflects the progressive relationship of the thesis objectives. However, each chapter is also designed to be complete as a case-study. Therefore, each case-study chapter has aims, some of which address thesis objective. Furthermore, each case-study chapter contains sections on literature review, methodology, and results and discussion. Whilst the sections are specific to the case-studies, some case-study chapters share parts of their methodology, and the shared parts are covered in Chapter 3. Therefore, Chapter 3 also serves to foreground the case-study chapters. Chapter 3 introduces SD, focusing on the modelling process, relevant concepts, language and validity. Secondly, a framework for SA that utilises simulation is proposed, and it will be demonstrated in the case-study chapters with SD as the simulation method.

Chapters 4-8 are the case-study chapters, and aim to address the research objectives 3-7 respectively. Chapter 4 aims to develop a valid simulation model of a supply-side RES from the bottom-up using SD. Therefore, Chapter 4 demonstrates supply-side modelling in EP. Chapter 5 then uses the model from Chapter 4 to demonstrate some typical analyses used for decision-making in CEP. Specifically, Chapter 5 demonstrates technical, economic and environmental impact analyses of different configuration of supply and storage technologies in residences, as well as different tariff options.

Demand-side modelling in EP is demonstrated in Chapter 6. Chapter 6 aims to develop a valid simulation model of a demand-side RES from the bottom-up using SD. Subsequently, Demand Side Management (DSM) is modelled in Chapter 7 by building on the demand-side model from Chapter 6, and different DSM strategies are explored to facilitate decision-making. Therefore, Chapter 7 demonstrates demand-side analyses and decision-making in EP.

Chapter 8 discusses how multiple RES combine to form ICES, as well as how the demand-side and supply-side system models integrate, and this highlights the modularity and hierarchy of systems. Other forms of combination, like aggregation, is also discussed – in the context of decision-making at community-level. Having RES as subsystems in the case-studies also provides opportunity to explore analyses and decision-making that can be done at residence-level. Chapter 9 concludes the thesis with an overview of the preceding chapters, and then answers the research question. Thereafter, reflections are presented on the strengths, limitations and insights from the case-studies; which is research objective 8. Finally, the thesis is concluded with discussion on future research.

2 Literature Review

2.1 Introduction

The aim of this chapter is to address the first three thesis aims which are: to explore SA for CEP; to explore the methodologies used in CEP which facilitate participation from multiple stakeholders; and to propose a SD-centred methodology for CEP, and identify gaps in the literature that demonstrate SD in the constituent methods. Ahead of these, SD will be introduced in the next section.

SA will be explored broadly, then the process of CEP will be explored in-depth. For both SA and CEP, utilised methods, methodologies and tools will be explored, but more in-depth with CEP because a methodology for CEP will be proposed in this chapter. Methods refer to specific activities, tools are aids to perform activities, while methodology is a structured set of activities to carry out research or interventions or activities [51]. To address the aim of exploring SA for CEP, two steps will be taken: discuss SA in general; then argue that CEP incorporates SA. Therefore, the issues discussed under SA are with a view towards highlighting the parallels between SA and CEP. Finally, a SD-centred methodology will be proposed for CEP, and the gaps in the demonstration of SD will be identified, which will be demonstrated in subsequent case-study chapters.

2.2 System Dynamics

2.2.1 Introduction

2.2.1.1 *What is System Dynamics?*

System Dynamics (SD) has its origin in the theory of nonlinear dynamics and feedback control developed in mathematics, physics, and engineering, by Jay Forrester at MIT in the 1950s [72]. System Dynamics (SD) is referred to both as a method and as a methodology, even within the same work as in [34]. As a method, SD is used within a methodology to model and simulate complex systems with features such as feedback, nonlinearity and delay, and these features lead to dynamic behaviour which can be analysed over time based on the principles of system structures [72], [76]. As a methodology, SD follows a guideline that can be utilised to solve a problem [72], [77]–[79].

SD is a quantitatively rigorous Systems Methodology [70]. By using the generic language of systems as outlined in the system principles [80], SD provides a common means of model representation and communication across several disciplines and beyond formal disciplines which makes it an interdisciplinary, as well as a transdisciplinary method. Therefore, the advantage of using SD includes aiding communication of a model's dynamics in the language of systems even without expertise in the modelled domain, and also the ease of integration with other SD models of other systems.

2.2.1.2 *Aims*

All System Dynamics models have at least one of two general aims: to improve understanding of a system by explaining its dynamics; and to virtually simulate and analyse possible configurations of the system [72]. These aims can be achieved via different architectures which include, but are not limited to, Ordinary Differential Equations, Agent Based Modelling, Discrete Event Simulation, or a combination thereof [71], [72].

2.2.1.3 *Systems and Complexity*

A system is a grouping of elements – interconnected – with a common purpose [81]. Alternatively, a system is "a group of functionally interrelated elements forming a complex whole" [72]. There are two sources of complexity in any system [72]: detailed complexity; and dynamic complexity. Detailed complexity arises from elements that are made up of other elements aggregated linearly. Dynamic complexity arises from relationships among elements (and beyond the system) which are characterised by feedbacks, non-linearity and delays (often simultaneously). Dynamic complexity is responsible for behaviour considered 'unintended consequences' or 'side-effects' or 'policy resistance'. Real systems often exhibit dynamic complexity [72], [76], [82], which SD is able to model. Whereas detailed complexity requires many elements, dynamic complexity may be present in systems with few elements.

2.2.2 Feedback

Causation in SD is not defined in the strict standard of science. Causation refers to the relationship between a change in one variable and the effected change in another variable. Causation is structural, while correlation among variables will emerge in the behaviour of the models when simulated [72].

A feedback is an arrangement of elements in a system where the future value is affected by the present value; a process where a cause reaffects itself in time [83]. A feedback loop may be continuous or discrete; as would be applicable to a population system or a programmable heating system respectively. In both feedback systems, information about the system state is taken and decision are made about the future. Systems with feedback are also called closed-loop systems [83].

SD literature has been found to be biased towards systems with continuous feedbacks, and this perhaps explains why bottom-up simulations have been unexplored because they are likely to have discrete feedback. One of the most valued benefits of using SD is the ability to improve understanding of the dynamics of a system by leveraging the rich research in generic system structures and feedback loops (e.g. reinforcing loops, balancing loops, s-shaped loops). In such cases, the modelling process typically begins with a dynamic hypothesis from a mental model, then a valid simulation model exerts confidence in the model, then exploring the model improves the users' mental model of the real system, and the SD model is continually improved with new understanding from the real system, and the learning feedback goes on. Such applications are especially suitable for social and natural systems, which are continuous. However, in the case of 'artificial' systems managed by computer programs (discrete), the system's rules are typically well understood and therefore the main benefit of SD is in providing a virtual 'flight simulation' environment, in addition to the other benefits mentioned previously. Ultimately, SD is a tool that should be applied knowing its benefits and limitations to the problem-type (or problem context). The application of SD in this thesis involves discrete feedback and the aim is a virtual 'flight simulation' environment.

2.2.3 Causal Loop Diagram: The Language of Systems

SD models can be presented diagrammatically using Causal Loop Diagrams (CLD) and Stock and Flow Diagrams (SFD). Figure 3 shows a simple Causal Loop Diagram (CLD) with three components of a system. The arrow shows the relationship between two components which is causal or dependency, depending on the reference component; causal relationship in the direction of the arrow, and dependency in the opposite direction of the arrow. Therefore, Figure 3**Error! Reference source not found.** shows that Production Rate and Shipment Rate cause, or affect, the state of inventory. Alternatively, the state of inventory depends on, or is affected by, Production Rate and Shipment Rate.

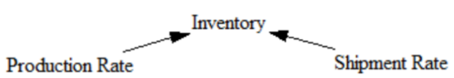

Figure 3 – A simple Causal Loop Diagram (CLD)

2.2.4 Stock and Flow Diagrams: The Language of SD

Figure 4 shows the SFD of a factory process on the left and a mirrored key on the right. The diagram shows inflow (production) and outflow (shipments) to a stock (inventory); inflows and outflows are flows. The variables in SD are mainly categorised into stocks or flows; others are auxiliary variables and constants. Stocks are represented as rectangles, flows as valves on double arrows, and other variables as text. Links between variables can be material links or information links represented as double arrows or single arrows respectively. The direction of material links indicate the movement of the same quantity between two variables as well as dependence, but information links simply indicate dependence. Stocks are accumulations, e.g. bank account, product inventory, employed people. Flows are the rate of accumulation, e.g. rate of savings and rate of spending; rate of production and rate of shipment; rate of hiring and rate of resignations, firing, redundancy or retirement. A source or sink are stocks that are outside the model boundary. Mathematically, these symbols are expressed in ***Error! Reference source not found.***, ***Error! Reference source not found.***, and ***Error! Reference source not found.*** where x and y can be any variable (stock, flow, auxiliary, or constant) and n is a natural number. Diagrammatically, the terms of integration in ***Error! Reference source not found.*** are connected to the stock via material links (double arrows), whereas the terms in ***Error! Reference source not found.***, and ***Error! Reference source not found.*** are connected via information links.

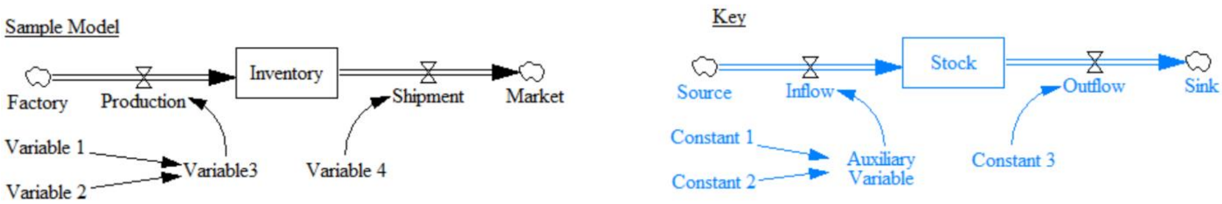

Figure 4 – Notation of Stock and Flow Diagram (SFD) adapted from [72]

$$Stock(t) = \int_{t_0}^{t} [Inflows - Outflows]dt + Stock(t_0) \qquad \textit{Eq. 2.1}$$

$$Inflows\ or\ Outflows = f(x_1, \dots, x_n) \qquad \textit{Eq. 2.2}$$

$$Auxillary = f(y_1, \dots, y_n) \qquad \textit{Eq. 2.3}$$

2.3 Sustainability Assessment

2.3.1 Impact Assessment

Based on [84]–[90], Sustainability Assessment (SA) can be summarised as a structured process of evaluating plans, policies and activities to identify implications on sustainability. SA may be confused with other assessment methods. In navigating SA literature, "the alphabet soup of acronyms currently makes for a confusing picture" [91]. In addition, there is no consensus in even the widely used acronyms like Integrated Assessment (IA) [92], however 'integrated' is used in at least one of two ways: either to refer to extension of scope as in [84], or to combine disjointed parts, as in [93]. Even so, it is likely to conflate IA with SA because the literature seems to be divided on whether SA is an IA, as in [84], [93], or not, as in [86], [89]. The distinctions are ontological, epistemological and methodological according to [86], or comprehensiveness and strategicness according to [89]. However, there appears to be no contention that both SA and IA are impact assessments.

More generally, there have been distinctions between SA and traditional impact assessments. Traditional impact assessments like Environmental Impact Assessment (EIA) and Life Cycle Assessment (LCA) have been considered environmental accounting that lack integratedness based on the framework in [94]. Alternatively, [89] distinguishes EIA and SA as two extremes in the spectrum of their framework with three dimensions of strategicness, comprehensiveness and integratedness, with SA rated higher in all dimensions. The 'distance' between traditional impact assessment and SA could be used as an evolutionary path, although the authors did not use the framework this way. In addition, [95] considers four principles: SA seeks multiple reinforcing gains in decision-making; SA reflects the complexity of socio-ecological systems; SA has a long-term view; SA seeks explicit attention to trade-offs.

2.3.2 Measuring Sustainability

2.3.2.1 *Sustainability*

Since SA identifies implications on sustainability, what is sustainability? The definition of sustainability has direct implication on how SA is measured. The definition, planning and measurement of sustainability has been a difficult problem lacking consensus [84], [96], [97], and the lack of consensus is considered desirable by some [85] who see it as an advantage that facilitates discussions, assuming there is some clarity at the conceptual level. In addition, [98] considers the changing concept of sustainability as a strength that keeps it relevant. Sustainability definitions and contestations of the definitions are characteristic of the field [99], and as a result, the concept of negotiated understandings of sustainability (among practitioner, researcher and stakeholder) is gaining acceptance [85], [93], [100]. Consequently, there are a variety of definitions of sustainability with a variety of interpretations. Since sustainability is value-laden and normative [101], the variety can also be seen as a reflection of that.

In this work, sustainability and sustainable development will be used interchangeably because the two are inextricably tied in SA literature and practice; technically, the former is a goal while the latter is the means. The anchor-point for the definition of sustainability is from the 1987 Brundtland Report as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [102].

Subsequently, many interpretations of sustainability have been proposed with varying emphasis. For example, whereas the Brundtland Report can be understood as proposing two pillars (environment and development concerns) [84], most interpretations are based on a definition with three pillars. For example, the Tripple Bottom Line (TBL) model which emphasises the environment, economy, and society; environment may be called ecology. TBL emphasises equal importance on environmental, social and economic considerations in decision-making [84], [97]. TBL is illustrated as three intersecting circles.

In contrast, the Deep Green Ecological Model represents the three pillars as concentric circles, with ecology being the innermost, then society and then economy. The Deep Green Ecological Model emphasises: the finite nature of the source and sink functions of natural resources; threshold; the steady state; carrying capacity; interdependence between ecological processes; and the idea that the socio-economic sub-system is embedded within the global biophysical system [97]. It is also known as the Ecological Model [94] or Limits Model [103].

Other interpretations with three pillars include the economic interpretation, and also the thermodynamic and ecological interpretations [94]. The economic interpretation emphasises the idea of social welfare and the external environmental costs associated with economic activity, as well as the principle of intergenerational equity. On the other hand, the thermodynamic and ecological interpretation emphasises the idea that the ecological interpretation of sustainability is situated in the context of the entropic nature of economic-environmental interactions. More recently, a fourth pillar has been introduced (environment, economy, society, institutions), which emphasises the balance or integration of the pillars. This interpretation is referred to as either the integration model [103] or the public policy and planning interpretation [94].

2.3.2.2 *Sustainability Indicators*

Indicators are rarely defined in SA literature, even in a study about indicators, for instance [104], because it is assumed that their meaning is not controversial. Four understandings of indicators were surveyed in [28] by focusing on their utility: indicators represent values of stakeholders since we measure what we care about [105]; indicators summarise and 'condense' the complexity of a dynamic problem into human understandable information [106]; indicators simplify, quantify, analyse and communicate complicated information [107]; indicators focus attention and simplify problems [108]. In addition, “We measure what we value, and value what we measure”, which are the indicators [109].

Indicators are measurable variables that represent attributes of a system, which could be individually measured or in combination [110]; for example energy output and GDP. Where indicators are numeric, a reference value such as a threshold is required to make sense of what the measured indicator represents [111]. Indicators can be used for trend analyses, forecast, early warning, setting goals, communication, and decision-making [28]. Other uses of indicators include benchmarking, diagnosis, decision-making and monitoring [104].

Therefore, indicators rely on conception (which is infused with values) before quantification. In the case of sustainability, the interpretations of sustainability determine what is quantified. Given that the most popular conception of sustainability is the TBL, the most common categorisation of SA indicators are economic, social and environmental [26], [112]–[116]. Some studies add a category for technical indicators [113]–[115], or resource indicators [112]. Others have categorised SA indicators along a different dimension as either a core indicator or complimentary indicator [104].

It is a challenge to SA that there is no consensus on the criteria for selection of indicators. However, being relevant is a recurring criterion [115], [117], [118], and being measurable is implied by the definition of an indicator. Other criteria are that an indicator should be scientifically sound, feasible, effective, pragmatic, accessible, understandable, reliable and have long-term view [115], [117], [118]. A methodology for identifying local energy sustainability indicators were explored in [104]. Also, an attempt was made to develop a theory for indicators in electricity generation expansion [119].

Indicators, usually in a combination, are used extensively to measure sustainability and are even regarded as tools of SA [86], [96], [120], [121]. However, given the complexity and multidimensionality of sustainability, multiple indicators are usually combined to arrive at a Composite Indicator (CI) [113]. The CI has been defined as "an aggregation of different indicators under a well-developed and pre-determined methodology" [110]. The process of 'combining' indicators to composite indicators typically involves five steps: Formulation strategy; scaling; normalisation; weighting; and aggregation [28]. The methods used for the combination of indicators explored include PCA [113], [122]; ASPID [112], [115]; MCDA [118], [123]; and content analysis [117]. However, they fall short of achieving or preserving the correlation among indicators in the composite indicator [110].

2.3.3 Process, Methods and Tools

2.3.3.1 *SA Process*

Due to the political and normative characteristic of sustainability, a step-by-step instruction to arrive at the single optimum solution cannot exist, however the process of SA could be made transparent, well-informed and normatively operational [101]. Table 2 shows a survey of the procedural stages of SA in [93], [95], [124]. The stages have been aligned horizontally for similarity, not equivalence, and vertically for procedural order.

Order	[95]	[93]	[124]
1	Decision to conduct a sustainability assessment (screening).	Screening: Determines which PPPs are to be subject to assessment.	Identifying appropriate purposes and options for new or continuing undertakings.
2	Identification of the desired outcome and hence the sustainability assessment decision question to be addressed.	Scoping: Establishes the Terms of Reference.	-

3	Establishment of sustainability goals and criteria for the decision (scoping).		Assessing purposes, options, impacts, mitigation and enhancement possibilities, design implications, implementation plans, etc.
4	Identification of alternatives and options to achieve the desired outcome.	Preliminary and detailed assessments.	
5	Prediction and evaluation of the impacts of each alternative.		
6	Selection and enhancement of the preferred alternative (mitigation).		Choosing (or advising decision-makers on) what should (or should not) be approved and done, and under what conditions.
7	Approval decision and announcement.		
8	Implementation and monitoring (follow-up).	Monitoring and ex post evaluation	Monitoring, learning from the results and making suitable adjustments.
9	-	-	Integrating the whole package, including linked strategic and project level processes, into a broader regime that evaluates the status of efforts to move.

Table 2 – Survey of SA process aligned across references

2.3.3.2 SA Methods and Tools

There are several descriptive frameworks as well as prescriptive frameworks of SA tools; the descriptive frameworks can be used to explore the categorisation of the tools, while the prescriptive frameworks can be used in selection of the tools. Tools and methods are used interchangeably in these frameworks. Studies often present descriptive and prescriptive frameworks in the same study, and it has been found that some prescriptive frameworks can be used as descriptive frameworks and vice versa.

SA tools/methods were categorised into three broad groups [121]: indicators and indices; product related methods, which focused on product life cycle; and Integrated Assessment, which are methods focused on policy and projects. The three groups were also arranged in order of temporal focus: indicators and indices being most retrospective, while integrated assessments are most prospective. Examples of indicators and indices includes Human Development Index, Sustainability National Index, and Environmental Pressure Indicators. Examples of product related methods include Life Cycle Assessment, Life Cycle Costing and Product Energy Analysis. Examples of Integrated Assessment methods include Impact Assessment, Uncertainty Analysis, System Dynamics and MCDA.

In another study [86], two descriptive frameworks are presented. The first is a framework with seven criteria represented by the vertices of a heptagon, and the three levels of the criteria by concentric heptagons. The criteria are: boundary-orientedness; comprehensiveness; integratedness; stakeholder's engagement; scalability; strategicness; and transparency. The second framework focuses on the integratedness of SA tools, which categorises tools used for SA into three groups: general methods for decision support; bio-physical, economic and social tools; integrated tools (e.g. HDI, GPI, LCSA). The three groups also form a spectrum from general methods for decision support to methods specifically developed for SA (integrated tools). Interestingly, the first of the two frameworks could be used as a prescriptive framework by considering the seven criteria as targets for the ideal SA tool.

Finally, [96] provides a typology, a descriptive framework, and a prescriptive framework of SA tools. The typology shows three broad groups of tools: biophysical tools; indicator tools; monetary tools. The descriptive framework, which was based on an earlier work [125] by the authors, identifies six dimensions which could be used to locate/identify SA tools: tool family; tools; concept of value; valuation perspective; role of participant; stance on reductionism.

Similar to the heptagon from [86], the prescriptive framework identifies five desirable features of SA tools: integrated assessment; predictive assessment; precautionary assessment; participatory assessment; and distributional assessment. Conversely, these features could also be used in a descriptive sense. Furthermore, four proposals on SA tools selection were made: according to the desired perspectives of the assessment; according to the desired features of SA; according to the acceptability criterion adopted; and according to the values of affected stakeholders.

For [93], SA consists of a variety of assessment tasks which may require different technical methods with available alternatives for each task. Factors to consider when deciding on a method for a task are: the nature of the task; level of detail and accuracy required; consistency with methods of other tasks; resource requirements of the method; the confidence (transparency, intelligibility and credibility) it exerts on stakeholders and decision-makers. Furthermore, [93] distinguishes between simple and complex methods. Simple methods do not require specialist knowledge and mainly use existing data, while complex methods may require specialist knowledge and collection of data.

2.3.4 Other Issues

2.3.4.1 *Trade-Offs*

The aims of SA include promoting multiple gain (win-win) as well as making trade-offs explicit [95] by providing "a forum and framework for explicit attention to the key trade-offs" [126]. On the contrary, others suggest that trade-offs should be avoided while aiming for multiple gains [89]. A middle ground is that while theoretically undesirable, trade-offs are practically unavoidable [97], and so it should be anticipated. Conflicts (trade-offs) are inherent to operationalising sustainability, and therefore rational conflict management and deliberation is required [101]. Nonetheless, when trade-offs are managed poorly, the environment typically suffers socio-economic losses [95]. Furthermore, SA should not be assumed to be for the good of the environment [84], or any of the 'pillars' of sustainability because trade-off is inherent.

It has been cautioned that trade-offs should be considered as a last resort, not the assumed task [124]. However, trade-offs are encouraged by interpretations of sustainability, whether as the TBL model [97], [127], [128] among the pillars; or as the principle based model [84], due to possible conflict of principles or due to the fact that the principles would be related and not always in a positive relationship. Nonetheless, [84] presents principle based models as less amenable to trade-offs.

Another challenge is that even when dealing with trade-offs, the treatment is often inadequate; especially with regard to substantive trade-offs. There are two types of trade-offs in SA [95]: process-oriented trade-offs; and substantive trade-offs. It could be said that substantive trade-offs are explicit while process-oriented trade-offs are implicit and have significant effects on substantive trade-offs. It was noted in [95] that while only few SAs (practice) accounted for trade-offs in some processes of decision-making (DM), no SA has accounted for trade-offs throughout the complex DM process. Consequently, [95] recommends that SA should explicitly manage trade-offs incurred from the process internally, as well as trade-offs exercised at the point of decision externally. After all, according to [129]: "Clarifying such trade-offs lies at the core of decision-making for sustainable development."

The six Gibson Trade-off Rules [126] can be used to manage trade-offs within SA to guide choices of options, as well as how to go about considering the options. Rules 1, 3 and 4 guide choices of options, while rules 2, 5 and 6 guide consideration of the options. While the Gibson Trade-off Rules are useful for the two levels of trade-off, their adoption in SA practice is almost non-existent [95].

2.3.4.2 *Integratedness and Holism*

Having established that SA seeks to be integrated, it begs the question: integration of what? There are at least 14 meanings of integration, and seven types of integration [89]. The types of integration were grouped into two categories - technique integration and theme integration - with technique integration having four types of integration, while [93] mentions three types of integration. Table 3 attempts to identify the levels of integration by the different types of integration, and it could serve as ascending levels of integration. Since integration of themes can cause or encourage integration of methods [89], integration of processes may encourage integration of themes; in other words, a higher level of integration causing a lower one.

	Reference	
Level of integration	[93]	[89]
Methods	Horizontal integration of assessments	Technique integration (linking via frameworks, stretching thematic coverage, combining

		assessments and INTER-disciplinary team)
Themes	Vertical integration of assessments	Theme integration
Processes	Integration of assessments into decision-making	-

Table 3 – SA levels of Integration

Disjointedness – the opposite of integratedness – encourages reductionism while integratedness encourages holism. Disjointedness in SA can be attributed to three causes [124]: due to the use of separate methods for the different sustainability pillars; then due to TBL's emphasis on balancing and trade-offs which negates interdependence; as well as separate training of experts. These three causes of disjointedness could be mapped to the three levels of integration (Table 3), as methods, themes and processes respectively. It has also been confirmed that a TBL conception of sustainability discourages integration [86].

All the conceptions of integration signify a move from a more disjointed/reductionist SA to a more integrated/holistic SA. However there appears to be a tension between becoming holistic and limits imposed by the underlying conception of sustainability. For example, [95] shows that even though objectives of sustainability may reflect its integratedness, the indicators derived from the objectives regress to being compartmentalised by TBL. After all, the conception of sustainability as separate pillars (TBL) emphasises their competition rather than their linkages and inter-dependencies [84].

Sustainability science has been proposed as an escape from a reductionist towards a holistic approach to problem-solving in [130]; normal/traditional science is inherently reductionist. The imperative to study complexity and dynamics is expanding the focus on the object of study from components of sustainability to the relationship between the components [86]. In other words, SA is moving towards a systems approach.

2.3.5 Conclusion

So far in this chapter, SA has been explored as a form of Impact Assessment, using indicators along the pillars of sustainability, depending on the interpretation of sustainability, as well as other issues. Specifically, the following aspects were discussed: SA as an Impact Assessment; how definitions of sustainability affect measurement of sustainability; SI; process, methods and tools of SA; trade-offs in SA; and integratedness. These aspects of SA were chosen with a view to highlight the parallels with CEP, which will be discussed next.

2.4 Community Energy Planning

2.4.1 Introduction

In this section, CEP will be defined and the phases of CEP will be discussed. The focus will be on the aims of the phases, the groups of methods used in the phases, and the methodologies and tools utilised for the methods. As mentioned in the introduction of this chapter, the rationale for going deep to explore the individual methods is because one of the thesis aims to be addressed in this chapter is to propose a SD-centred CEP methodology, which requires discussing the methodologies and tools before showing how the proposed methodology might achieve similar functions.

2.4.2 CEP Phases and Challenges

Sub-national Integrated Energy Planning is presented as CEP when applied at the community-level [51] [52]. Therefore, CEP can be defined as [51]: “an approach to find environmentally friendly, institutionally sound, socially acceptable and cost-effective solutions of the best mix of energy supply and demand options for a defined area to support long-term regional sustainable development. It is a transparent and participatory planning process, an opportunity for planners to present complex, uncertain issues in structured, holistic and transparent ways, for interested parties to review, understand and support the planning decisions”. ICES is the outcome of CEP.

The four CEP phases outlined by Mirakyan et al. [51] is the same as in [131] and a synthesis of the processes outlined in [54], [132]–[135], each with different emphasis. Phase I is preparation and orientation, Phase II is model design and detailed analysis, Phase III is prioritisation and decision, and Phase IV is implementation and monitoring. While [132] demonstrates the first phase only, the authors' recommended approach to planning can affect all phases, with emphasis on process instead of fixed goals, on learning instead of predicting, on back-casting instead of forecasting, and on social learning and adapting to change. Earlier on, [136] had mentioned that EP should focus on process more than content. Three phases of planning were presented with emphasis on modelling/design tools in [133]. Six phases were presented in [134] with emphasis on assessment of the present situation, modelling/design tools, and case-studies that cover all the phases. Five phases were presented in [135] with emphasis on participatory processes and case- studies were presented per phase.

Furthermore, [54] covers the equivalent of the first two phases of CEP only. Four stages were presented in the following order: Community Master Plan (CMP); Community Regulatory Plan (CRP); Community Site Plan (CSP); and Architecture Design (AD). The first two stages take a top-down approach while the latter two take a bottom-up approach to planning. In a top-down approach, the planners refer to standards based on other communities, then set targets to achieve. The bottom-up approach describes the technologies and built environment as models, then carries out analysis.

Across the four phases of CEP, there are three levels [51], which is illustrated in Figure 5. The participatory level identifies groups of participants which could include steering committees, interested parties, and planners and experts. The process level involves the planning steps, activities and tasks. The methodical level involves the analytical and procedural tools utilised; procedural tools are utilised for participatory and decision-making processes. Phase IV does not contain a methodical level because it relies on quality control standards.

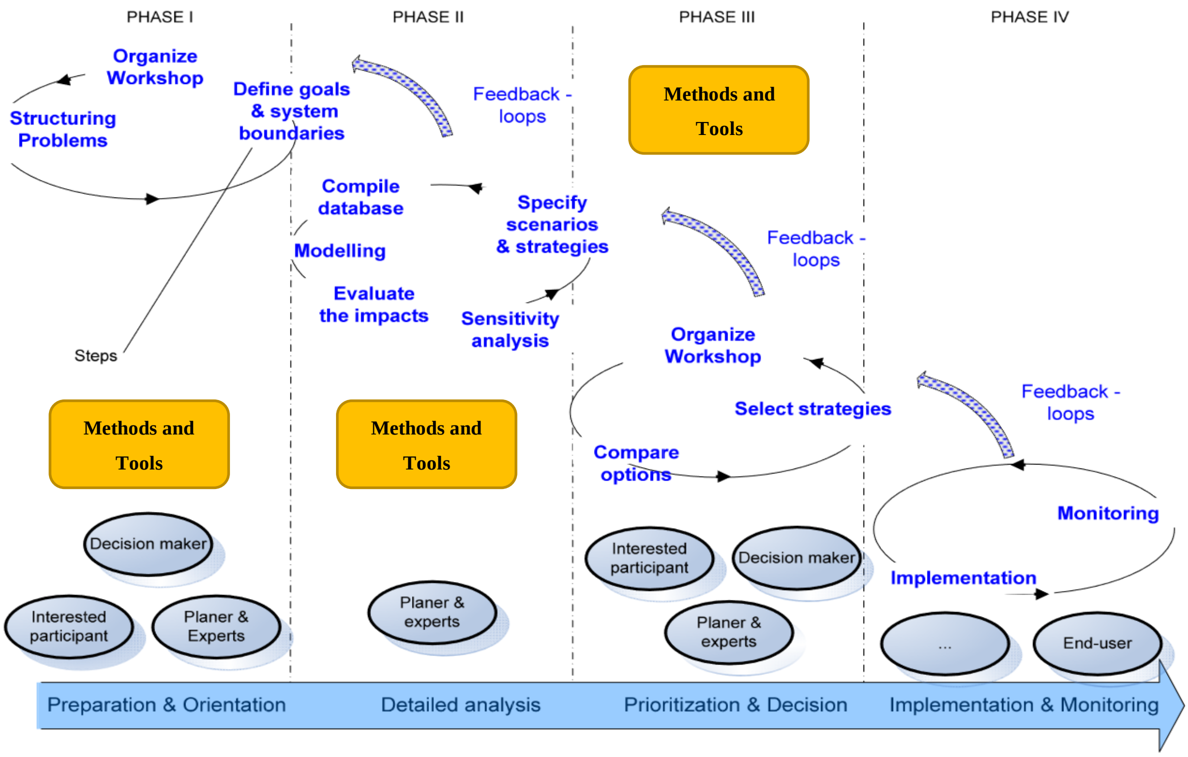

Figure 5 – The four phases of CEP from [51]

Each phase is iterative (see Figure 5) and so the outcomes can be updated. Whilst output from a phase serves as input to the subsequent phase, there is feedback between the phases (in reverse). Each of the four CEP phases have objectives [131]. The objectives in Phase I are three: to analyse the initial situation; define problems and goals; and "involve and help interested participants to understand the planning issues and to understand each other better". The objective in Phase II is to create a model of the energy system for analyses e.g. scenario analysis, impact analysis, sensitivity analysis. The objective of Phase III is to present the analyses from previous phases in a workshop to interested participants with three expected outcomes: prioritise options; obtain consent; and develop strategies for implementation. Finally, the objective of Phase IV is to assess the implementation of the strategies agreed in Phase III and generate feedback to the previous phases.

Figure 6 shows groups of methods used in each phase, based on [51], [131], [132], [137]. Therefore, Figure 6 illustrates the CEP methodology in terms of groups of methods. Phase I methods are mainly Problem Structuring Methods (PSM), Phase II are mathematical modelling methods, Phase III are decision-making methods, Phase IV does not have a group of methods but may rely on quality standards for monitoring and feedback. A method within CEP could be carried out by a tool (especially specialised software), or a stand-alone methodology that is appropriated for an activity in CEP. An example of a tool would be HOMER software for energy modelling, and a methodology would be SD.

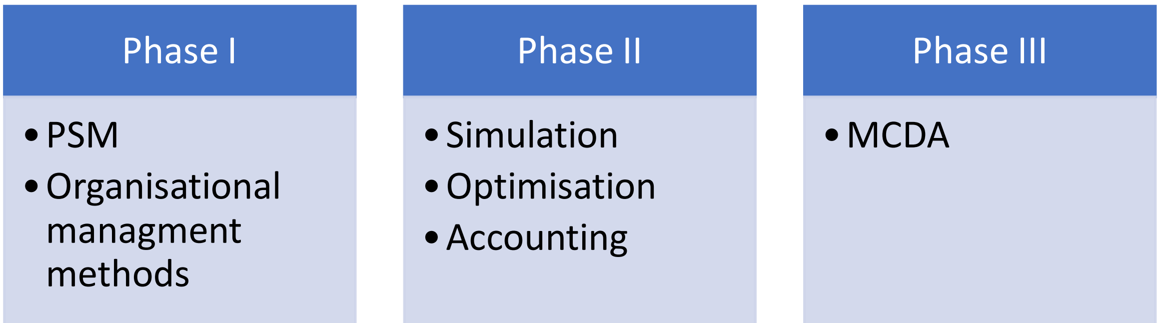

Figure 6 – CEP Methodology presented as groups of methods in the phases of CEP

In Phase I, Problem Structuring Methods (PSM) aim to clarify situations that are complex, uncertain, or internally conflicting. Organisational strategy and management techniques like SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis and SMART (Specific, Measurable, Attainable, Relevant, Time-bound) have been used in Phase I [137]. However, PSM are more appropriate for CEP because of their capability to clarify 'wicked' or 'messy' problems [131]. Therefore, organisational management methods will not be considered further.

In Phase II, simulation, optimisation and accounting are categories of mathematical models. In Phase III, Multiple Criteria Decision Analysis (MCDA) are groups of methods used to identify the optimal decision given multiple and/or conflicting criteria. Phase IV does not utilise a distinct group of methods but instead relies on quality standards. Example of quality standards include International Organization for Standardization (ISO) 14001 which includes Environmental management, Life Cycle Assessment, Principles and framework [51]. Another quality standard is the EU Eco-Management and Audit Scheme (EMAS) [51].

The variety of methods required for CEP leads to a disjointed CEP methodology, because of the atomistic approach of having separate tools or methodologies for different method, and that presents two challenges. The first challenge is a hindrance to the holistic approach of CEP and holistic understanding of the resulting system, when different frameworks are used to understand different aspects of the system. Since CEP aims to be a holistic approach [51], a more holistic approach would utilise fewer tools or methodologies for all the methods, as well as prioritise synergy and integration among methods in the choice of tools and methodologies. Taking the 96 energy tools reviewed in [66] and [138] for examples, none was found to be used for PSM (Phase I), or integrated with MCDA (Phase III); although some combined simulation and optimisation (both in Phase II) modelling. Addressing this challenge would also lower the barrier for modellers using one method to learn to model using another method.

The second challenge is that the participatory aim of CEP is hindered because of difficulty in communication that would result from different experts working on different methods using different tools. Transdisciplinary research is still possible at the level of inputs and outputs to these methods but there is no transparency in the process of the methods. For example, the results of analysis from a simulation model could be presented to participants from various backgrounds to make a decision, but the participants cannot inspect the model which makes the models black-boxes to them. Having models that are not black-boxes can improve transparency, facilitating communication among participants, and thereby improve possibility for transdisciplinary research. These challenges present an opportunity to propose a comprehensive methodology for CEP which could address them.

Having introduced the CEP phases and the group of methods in the phases, subsequent sections will explore some of the methodologies and tools which can be used as methods in CEP. The methodologies and tools will be discussed in phases, and the scope of methodologies will be limited to those that are either similar to SD, or combined with SD, or implemented in CEP, whereas the scope of tools includes any tool that implements the methods required in CEP. Eventually, SD will be argued to be an effective alternative to some of the methodologies and tools. Therefore, the focus will be on exploring PSM for Phase 1, simulation and optimisation methods for Phase II, and MCDA for Phase III.

2.4.3 Phase 1: Problem Structuring Methods

2.4.3.1 *Introduction*

The participatory nature of CEP makes the process 'messy' because of the multiple stakeholders who may have varying interests and perspectives. Therefore, the problem needs to be 'structured' first to achieve clarity, resolve conflicts, and possibly even some level of consensus prior to seeking solutions to the problem [139]. PSM, also known as Soft OR or Soft Systems refer to "a group of methods that focus on the effective structuring of a problem situation rather than solving it" [30]. The methodologies that will be explored are OTSM-TRIZ (Russian acronym for the General Theory of Powerful Thinking), Soft Systems Methodology (SSM), Soft System Dynamics Methodology (SSDM) and Mediated Modelling (MM). Furthermore, PSMs in general have been shown to aid in structuring MCDA (Phase III) since the 1990s [140], [141]. Therefore, combinations of the PSM with MCDA will also be highlighted.

2.4.3.2 *OTSM-TRIZ*

In the 1940s, Genrich Altshuller proposed a problem solving methodology to arrive at solutions to a problem with minimal trial and error, and in the 1970s, the method became known as TRIZ (Russian acronym for the Theory of Inventive Problem Solving) [142], [143]. The methodology was the result of analysing thousands of patents, then categorising them based on their problem-solving processes [143], [144]. The aim of TRIZ is to resolve a problem while avoiding the trial-and-error approach, which saves design time and cost. The tools of TRIZ are mainly ARIZ, which is an algorithm for addressing inventive problems in engineering, and tools to improve the efficiency of ARIZ [142]. The improvement tools include the 40 inventive principles, 76 standard solutions, separation principles, contradiction matrix, Ideal Final Result, function analysis, substance-field, nine windows, creativity tools, and ARIZ [144].

To address the limitations of TRIZ in non-engineering problems that are interconnected, OTSM-TRIZ was proposed by Altshuller later in the 1970s [142], [143]. OTSM-TRIZ therefore serves the function of PSM while having the same aim as TRIZ. TRIZ and OTSM-TRIZ were compared using a case-study for the development of a new type of gondola for stratospheric ballooning, focusing on the three steps of TRIZ which are identification of problems, extraction of disclosed and hidden contradictions, and identifying solutions [142]. While TRIZ remains an effective tool for problem solving, OTSM-TRIZ improves on TRIZ by providing tools to structure complex problems where the problems are interconnected; TRIZ identifies problems but OTSM-TRIZ organises the problems in hierarchy, as well as their relation [142].

OTSM-TRIZ was combined with MCDA in [131] where OTSM-TRIZ has been used to structure data in CEP [131]. The objectives that were assessed in the MCDA were identified and prioritised (as a hierarchy) using OTSM-TRIZ. The outcome is that the effectiveness of the MCDA was improved significantly.

2.4.3.3 *SSM*

SSM is perhaps the most widely used PSM [31], which looks into situations with 'multiple actors; multiple perspectives; incommensurable and/or conflicting interests; important intangibles; and key uncertainties' [139]. SSM was first proposed by Peter Checkland in the 1980s as a response to the ineffectiveness of the henceforth Hard Systems Thinking to real-world problems [69] [34].

In terms of theoretical premises and philosophical foundations, SSM is among the most developed systems methodologies [31]. Whilst Hard Systems Thinking assumes that systems exist in the real world, SSM departed from that and posits that systems exist in the minds of individuals as abstract concepts [69]. Hence SSM is epistemologically interpretive [69], [145]–[147]. The utility of the abstract concept of 'systems' is to help people cope with the varied perceptions they might have of a highly interconnected real world [31].

SSM is implemented in seven sequences of activities which are, as articulated in [59]*:* (1) enter the situation considered problematical; (2) express the problem situation; (3) formulate root definitions (CATWOE) of relevant systems of purposeful activities; (4) build conceptual models of the systems named in the root definitions; (5) compare models with real-word activities; (6) define possible changes that are both desirable and feasible; (7) take action to improve the problem situation. The seven steps are located in the real world and in the abstract world where Systems Thinking happens about the real world. Steps 3 and 4 are in the abstract world but lead to actions in the real world which changes the state of the real world, and that requires updating the Systems Thinking about the real world and so on.

Whilst the SSM process has since been extended [146], the original seven steps of the method has remained useful and applicable. An example of an extension is the two-strand model which proposes an enhanced cultural analysis; Analysis 1, 2 and 3 [146]. Analysis 1 considers the actors in the intervention, Analysis 2 appraises the roles, norms and values, and Analysis 3 considers the politics of the situation.

In relation to other PSM, SSM has been combined with other methodologies like TRIZ [144], Value Focused Thinking (VFT) [59] and System Dynamics (SD) [31]. SSM and TRIZ were combined in a simulation of an infrastructure megaproject [144]. The strength of SSM is that it provides a holistic understanding, including perspectives from different actors, while the strength of TRIZ is the ability to identify and aid in resolving contradictions (as well as employing the concept of ideality). SSM and TRIZ reinforce each other with their strengths. SSM was used to identify the problems holistically, then TRIZ was used to generate innovative solutions from the identified contradictions, and finally SSM was used to evaluate the solutions.

Similar to OTSM-TRIZ, SSM was combined with MCDA to structure multi-objective problems prior to applying MCDA [57]–[59]. In a study, SSM was applied to an environmental decision-problem with multiple stakeholders by a public transport company [57]. In another study, three Information and Communication Technology projects were used as case-studies to demonstrate the value of SSM to MCDA [58]. Finally, SSM was also used to generate a 'cloud of objectives', then VFT was used to structure the objectives in a hierarchy, which was then used as objectives in MCDA [59].

2.4.3.4 SSDM

SSM was combined with SD and a new methodology was proposed called Soft Systems Dynamics Methodology (SSDM). SSDM is regarded as a standalone systems methodology that is the result of a combination of two methodologies from different systems thinking paradigms [31]. Although SD encompasses SSM, SSM outlines problem structuring procedures in more detail than SD. The type of combination of the systems methodologies, SD and SSM, can be described as multi-methodology [148], which is when parts of a methodology are combined. The main contribution of SSDM is the 10-step framework it provides and there are two ways to understand the framework. One way is that it generally follows the seven steps of SSM but utilises SD to model the problems, validate the model and identify interventions that can lead to desired change (steps 5-7 of SSM). Like SSM and SD, learning as feedback from the exercise is emphasised in SSDM.

Another way to understand the SSDM framework is as SD but where the first step of problem articulation utilises some steps of SSM. In other words, SD in practice encapsulates SSDM, or SSDM can be understood as a specification of SD, because problem structuring is part of SD [32]–[34]. However, SSM cannot encapsulate SSDM because quantitative modelling is not part of SSM. Moreover, SD's epistemology has expanded from its functionalist beginnings to also being interpretive, whereas SSM remains interpretive [31]. SD has been widely acknowledged as a combination of soft and hard methods, whereas SSM is a soft method [32]–[34], [149], [150]. Therefore, this work considers SD to encompass SSDM and SSM. Other PSM have emerged from SD like Group Model Building (GMB) [32] and Mediated Modelling (MM) [35]. SD has also been demonstrated in combination with other PSM like cognitive mapping and interactive planning.

2.4.3.5 Mediated Modelling

Mediated Modelling (MM) is a participatory problem-solving methodology that utilises SD modelling [35]. MM was developed from GMB, but whereas GMB focuses on client groups, MM expands the participants to include stakeholder views [35]; which makes it more suitable for public projects promoting sustainable development. GMB also emerged from SD to involve client groups when building SD models, and GMB is considered as part of SD [32].Therefore, whether MM is part of SD or SD is part of MM, is a matter of perspective. However, MM requires SD whereas SD does not require MM.

"Mediated Modelling (MM) is based on System Dynamics thinking but emphasizes the interactive involvement of affected stakeholders in the learning process about the complex system they are in. It allows a group of stakeholders to understand how seemingly small decisions may spiral a system onto an undesirable course. Such understanding provides opportunities to jointly design strategies to abate the negative spiral or to curb a trend into a more positive one" [33]. MM combines the advantages of Soft Systems Thinking and modelling, where Soft Systems Thinking refers to the improved understanding of the dynamics of a complex problem [35]. MM should be utilised in complex problems with many dimensions; when conflict is anticipated among stakeholders, when collaboration is desired to solve a problem, or when consensus is desired. After all, MM supports the early involvement of stakeholders in decision-making processes [35].

Based on [35][33], there are two parts to MM which are problem structuring and problem solving. The problem structuring part involves establishing the boundaries of the problem, eliciting the different perspectives and highlighting the assumptions. The problem-solving part involves modelling the problem-situation based on the problem-structuring part, then understanding the system structures responsible for the observed problem, and then possibly agreeing on how to resolve the problem. Consensus building is a major benefit of MM.

Similar to previously discussed PSM, MM has been combined with MCDA in a problem of environmental decision in Portugal [35], where MM was used to structure the problem and identify criteria for decision-making. The case-study involved 13 stakeholder groups. Four workshops were held each lasting a day but the problem-solving phase was done in one workshop which lasted two days. The criteria were derived from the multiple perspectives of the stakeholders, and the criteria were also consolidated as consensus was formed which reduced the number of criteria and improved the decision-making process. Furthermore, MM was used to identify alternatives and their consequences using the SD model created.

2.4.3.6 Conclusion: SD as PSM

In exploring PSM, the following methodologies were explored: OTSM-TRIZ, SSM SSDM and MM. It has been argued that SSM, SSDM and MM can be understood as SD with emphasis on the soft side of SD especially when used as PSM. In other words, SD encompasses SSM, SSDM and MM. OTSM-TRIZ has been combined with MCDA, but SSM and MM have also been combined with MCDA. Therefore, combining SD with MCDA can be a substitute for combining OTSM-TRIZ with MCDA.

2.4.4 Phase II: Mathematical Models

2.4.4.1 *Introduction*

Taking a different approach from Phase I where methodologies were discussed directly, the mathematical models in Phase II are more complicated to navigate. The literature and practice emphasise modelling tools which implement certain methodologies and combine others. To navigate the mathematical models, a descriptive framework will be proposed, and SD will be located among existing tools. The classification provided by the framework will aid a clearer comparison between the state of the art and SD, which will be discussed in the conclusion of this section on Phase II.

2.4.4.2 *Classification of Mathematical Models*

A model is a simplified version of a real object or system made for a specific purpose. Models may be broadly classified into physical models, mental models and mathematical models [151]. An example of a physical model is a miniature building of a real building as used by building architects, or turbines used to mimic free fall for training skydivers. Mental models are our understandings of real objects/systems and processes, and may be represented using diagrams or graphical languages even though mental models are abstract. On the other hand, mathematical models use the language of mathematics to describe systems and processes. Phase I of CEP dealt with mental models, while Phase II is concerned with mathematical models.

EP literature uses the term 'model' to refer to both modelling tools and their products, as noted in [152], which leads to difficulty in understanding. In this work, model will be used as a simplified representation of an energy system [152]. A classification of mathematical modelling tools is proposed based on the classifications in [51], [53], [54], [66], [138], [151]–[154], even though some classify models not tools. It is hoped that this classification is more comprehensive for CEP and minimises overlaps. The classifications in [51], [53], [54], [66], [138], [153], [154] are one dimensional, even though [51], [53], [66], [138] had multiple one dimensional classifications e.g. by purpose, geographical scale, time scale, etc. Many of the dimensions are similar but user friendliness, reporting capabilities, and data management capabilities of bottom-up software packages were reviewed in only [53]. The only two-dimensional classification found is in [152] which classified by purpose in one-dimension then by multiple one-dimensions similar to the other classifications. The proposed classification in this work is three dimensional, by type of proprietary assumptions, then by modelling methodology, and then by focus of created models. The classification aims to locate all CEP modelling tools in one location only at the intersection of the three dimensions, avoiding overlaps.

The proposed classification is presented in Figure 7. In the first dimension, mathematical modelling tools may be classified based on the types of assumptions made by creators of the tools about the models to be created: energy software make assumptions about the models; while generic software do not. In the second dimension, the modelling tools may be classified into four based on their modelling methodology: optimisation; simulation; accounting; and hybrid. All the methodology-based classifications are present in each of the assumption-based classifications. The third dimension is the focus of the modelling tool; generic software do not have a focus dimension, and this will be explained. The first two dimensions will be explained initially without examples because all tools have at least two dimensions, then examples will be discussed in sections 2.4.4.5, 2.4.4.6 and 2.4.4.7. The third dimension will be explained with the examples of energy.

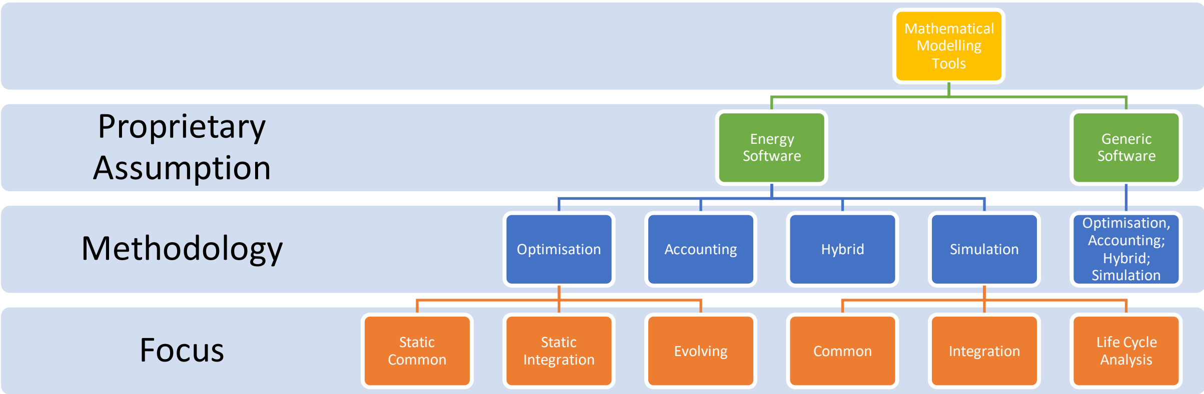

Figure 7 – Proposed classification of mathematical modelling tools

2.4.4.3 *First Dimension: Proprietary Assumption*

Energy software refers to software programs whose main purpose is to generate models of energy systems in which assumptions have been made about details of the models that will be created, but users have limited ability to alter configurations etc. On the other hand, Generic software are software whose tools are not limited to models of energy systems but instead are limited by the language or syntax of expression of the software e.g. programming language. Both can be used to generate models of energy systems but less effort is typically required with energy software when creating models of similar complexity. Ease of use perhaps explains the overwhelming popularity of energy software over generic software, which has led to multiple reviews of the former but none on the latter with regard to models of energy systems.

Unhindered by the internal assumptions of energy software, generic software allow model creators flexibility in deciding the boundaries of their models; for example by endogenizing variables that would otherwise impose undesired external assumptions, as found in energy software. Model creators enjoy more freedom with generic software which are only limited by the syntactic rules of the tool or underlying language. However, more expertise and time may be required.

2.4.4.4 *Second Dimension: Methodology*

Modelling methodologies may be optimisation, simulation, accounting or hybrid. Optimisation consists of describing three parts of a system: the objective; decision variables; and constraints [151]. Optimisation models essentially solve an optimisation problem for an energy system to attain an objective (e.g. minimise cost, minimise emissions by end of a year) by making choices on decision variables (e.g. utilised fuel) that are limited by constraints (e.g. maximum utilised fuel). The objectives, expressed as mathematical functions, may be multidimensional. Optimisation models are used to identify an optimal configuration or scenario in a system. Furthermore, optimisation models are prescriptive; that is, what should be done to reach a goal, assuming people always make the optimal choice. In other words, optimisation models tell you what to do to attain the best situation, given the assumptions; optimisation requires and assumes perfect foresight [151].

Simulation consists of describing two parts of a system: the state of the system at the beginning; and the behaviour of the system over time [151]. Simulation models are essentially time-based, and the behaviour of the system is simulated by calculating the system state in subsequent time-steps based on its previous state and exogenous variables, and so on until the end of the simulation time. Simulation models are used as virtual worlds that imitate the real world without the costs of real resources and time. Simulation models are descriptive; to answer "what-if", which clarifies what would happen in a given situation. In other words, simulation models tell you what will happen in a certain situation, given the assumptions.

Accounting consists of simply describing the relationship between variables of interest as equations. Accounting models are used to explore the cost implications of resources, environment and social decisions, without aiming for optimality or iterating over time-steps as in the case of optimisation software or simulation software respectively. Consequently, accounting software packages are simpler and typically quicker to model. Examples of variables of interest include energy requirement, costs, and environmental impacts. Accounting software may execute statistical operations and are often spreadsheet-based (also called ‘tool boxes’) [66], [138]. Accounting methodologies includes Life Cycle Assessment (LCA) and Physical/Environmental Accounting [51], [131]. LCA assesses the cumulative environmental impact (e.g. emissions) of a product, process or service throughout its life cycle. Physical

Accounting is similar to LCA but expresses environmental impact in monetary terms instead of environmental impact; it is considered part of Accounting discipline and it incorporates environmental and economic information.

Finally, hybrid modelling tools combine features from the three preceding groups. Hybrid models should be able to utilise more than one methodology. Names of sub-methodologies should not be taken as being hybrid methodologies; e.g. models that do simulation-based optimisation are considered simulation models, not simulation and optimisation.

Simulation-based optimisation (also known as optimisation via simulation) are important features of simulation models that allow for some of the benefits of optimisation models. Simulation-based optimisation aims to simulate all possible configurations of a model, and then select the configuration with the optimal outcome at the end of the simulations [155]. The outcome would be a variable that is calculated endogenously during the simulation, and an example of an optimal outcome could be least discounted cost. In practice, it may be inefficient to simulate all possible configurations, in which case meta-heuristic methods may be utilised if the set of possible configurations is large, otherwise direct comparisons or rankings are carried out. A decision tree of methods to use has been provided in [155] depending on the types of configuration variables. Furthermore, sensitivity analysis has been used as a first step to identify the most sensitive input variables, which are then used to define the limited search space for simulation optimisation [156].

2.4.4.5 *Energy Software – Focus Dimension*

The energy software featured in the following were narrowed down to those applicable to geographic scale of community. Within energy software, the four methodology-based classifications are further categorised by focus as shown in Figure 7. Optimisation software may be grouped into static optimisation and evolving optimisation. Static optimisation may be grouped into integration focused and non-integration focused. Similarly, simulation software may be grouped into common, integration, and Life Cycle Assessment (LCA). Integration focused software are primarily concerned with the integration of energy conversion technologies in terms of energy loss and energy balancing.

Optimisation problems are described as Linear, Linear Programming (LP), Dynamic (non-linear) Programming, or Mixed Integer Linear Programming (MILP). The focus groups of optimisation software in Figure 7 are Static Common, Static Integration and Evolving. In static optimisation software, all parameters – except decision variables – remain fixed e.g. energy demand, cost, efficiency, subsidies. On the other hand, evolving optimisation software are basically a series of back-to-back static optimisation models where some parameters (that were fixed in static optimisation) are specified to change during the optimisation. For instance, changes in the following may be specified: energy demand, cost of energy resources, innovation and efficiency of technology, taxes, and subsidies. Therefore, static optimisation software are used for short-term models (1 year) while evolving optimisation software are used for longer term models. Examples of static optimisation software are DER-CAM and EAM, while evolving optimisation software are MARKAL[157], TIMES[158], ETEM[159], OSeMOSYS[160], MARKAL/TIMES[161] and MESSAGE III[162]. All the static optimisation software listed are non-integration focused (Static Common in Figure 7), whereas an example of integration-focused (Static Integration in Figure 7) is OSMOSE[163].

Simulation models require input in terms of system configuration at time 0 and exogenous variables. The exogenous variables can be constants or time-series; after all, constant variables are the equivalent of an unchanging time-series. The energy system can include production (supply-side) and consumption (demand-side) that are determined endogenously, while the exogenous variables can include prices and other costs. The focus groups of simulation software in Figure 7 are Common, Integration and Life Cycle Analysis. Examples of common simulation software include EnergyPLAN[164] and HOMER[165], whereas those that are integration simulation software include H2RES[166] and EINSTEIN[167]. Examples of simulation software for LCA include GEMIS[168], Simapro[169] and Umberto[170].

An example of accounting software is RETScreen[171]. RETScreen[171] assess and quantifies energy conservation measures in projects. Finally, hybrid software combine more than one methodology, and therefore the purposes are more comprehensive than any individual group. For example, LEAP[172] combines features from all three groups: long-term optimisation with evolving variables; accounting calculations; and time-step simulation of system operations. Another example of hybrid software is MARKAL-MACRO[173].

Despite their differences, energy software have some similarities. For instance, all the energy software input similar data which are characterised as quantitative, monetary and disaggregated. Also, all energy software have a Graphical User Interface (GUI) and built-in reports that facilitate modelling. Another similarity is that all the energy software are used for comparative analyses, but different types. Optimisation software compare different scenarios/configurations to determine the least-cost paths of investment; where cost may be economic, environmental or energetic. Simulation software compare the impact/performance of different configurations and operation strategies; performance may be technical, economic, or environmental. Accounting software compare the financial feasibility of different configurations. Individual software vary in their time resolution and time horizon allowed for the analysis.

The reason why energy software can be categorised by the focus of the models they can create is because of assumptions that are embedded in the software by the developers of the software. Having a focus makes energy software more specialised, but also restrained in terms of flexibility to users (model creators). These assumptions will be discussed next.

2.4.4.6 *Energy Software – Assumptions*

According to Van Beeck [66] and Hourcade [174], energy software have internal and external assumptions. The internal assumptions determine the richness or detail of the model, while external assumptions refer to the implicit information contained in exogenous input. Four dimensions were provided for internal assumptions [174]: the degree of endogenization; the extent of the description of the non-energy sector components of the economy; the extent of the description of energy end-uses; the extent of the description of energy supply technologies. The internal assumptions can be understood as limiting the possible models that can be created by users of the software. Given the increased sophistication of energy software today, more dimensions can be added, especially regarding the extent of the description of model components.

Where exogenous input is provided to the model as a parameter, the input implicitly contains assumptions about other parameters. For example, population growth is directly proportional to increase in energy demand. Other examples of variables that are related include: economic growth and lifetime of equipment; energy demand and technology choice; and energy supply and rise of alternative supply. Where there is high degree of endogenization, these relationships may be specified implicitly in the model or energy software. However, the relationship is often not specified, in which case the model creator should be aware of this limitation.

The implication of internal assumptions on the model creator has not been explored further than presented (above) in previous studies. From the perspective of a model creator, the degree of endogenization can also be understood as determining the limit of user input. Energy software can be considered as a model-template from which model components are selected/deselected and properties are adjusted where allowed. Therefore, the model-template represents all the possible models that may be created from the energy software. Model-template has been referred to as the Reference Energy System or superstructure in [152].

Energy software also vary in the extent to which they allow exogenous variables, and therefore some are more extendable than others in different aspects of the super-model. Exogenous variables vary in sophistication from assigning constant values to model-parameters, to time-series input, to file input and ultimately to integration with other software. However, flexibility to model creators must be balanced with computational efficiency and the simplicity of using the software. Individual energy software would fall on a spectrum from "more" to "less" [66].

2.4.4.7 *Generic Software*

Theoretically, all that is required to create a mathematical model is the language of mathematics to describe the model. Since the model is only a means to analysis or insight, the mathematical description needs to be evaluated or solved. Therefore, any programming language that can execute mathematical statements can 'run' a model, theoretically. In practice, programming languages vary in their abilities to execute mathematical statements in terms of efficiency, accuracy and even range of mathematical expressions. To enhance ease of use of complex mathematical expressions and operations, libraries have been created within programming languages that take advantage of more basic mathematical operations which such languages execute efficiently. Furthermore, software applications have been created to further enhance usability, as well as to allow for other features useful to users; even programming languages are used via Integrated Development Environments (IDE) for projects. However, these software applications remain mathematical tools to the users, and they are Generic Software in Figure 7.

Some of the Generic Software found in CEP include MATLAB, Python, Vensim, iThink, and Anylogic. The most popular generic tool found in CEP (and EP in general) is MATLAB. The strengths of MATLAB include its matrix manipulation, vast library of efficient mathematical operations, ease of integration with programs from many programming languages, as well as its wide adoption. Whilst Python is a programming language, the variety of IDEs available for Python makes it an alternative to MATLAB. Python IDEs offer similar advantages with MATLAB but does not have the development and customer support available to MATLAB, because MATLAB is proprietary while Python is Open Source and supported by a community. Both MATLAB and Python are used in CEP independently or with other software tools, and all applications found in the literature are bottom-up approaches. Additionally, both tools can create optimisation, simulation and accounting models. Therefore, MATLAB and Python are hybrid tools in terms of methodology.

On the other hand, Vensim, iThink and Anylogic are simulation modelling tools only. They offer a graphical modelling interface on top of the text-based mathematical equations. Therefore, graphical models like Causal Loop Diagrams (CLD), which are used in a variety of Systems Thinking paradigms for mental modelling, can be created. However, to simulate the models, equations must be specified. All three Generic Software were designed specifically for System Dynamics modelling and simulations. System Dynamics (SD) encompasses three simulation architectures, and the software are able to create models in the different architectures to different degrees, with varying features and degrees of integration between the different architectures. The three fundamental architectures of SD are Ordinary Differential Equations, Discrete Event Simulation and Agent-Based Modelling (ABM) [71], [72]. All the SD software are mature in implementing differential equations which is the default SD architecture.

A Generic Software for accounting models would be a spreadsheet or database software e.g. Microsoft Excel. No application of a generic accounting model has been found in CEP. Generic Software that are specific for optimisation would be the optimisation engines and languages used by optimisation energy software e.g. GAMS (General Algebraic Modelling System) or GLPK (GNU Linear Programming Kit). Furthermore, depending on the purpose of a model, Generic Software may take a top-down or bottom-up approach, which will be discussed in the next section.

2.4.4.8 *Other Relevant Dimensions*

In addition to the proposed three-dimensional classification, there are other dimensions that are important to the thesis research question but do not fit neatly into the proposed three dimensional framework, because they would allow for multiple co-location of tools if added. These dimensions are analytical approach, supply-demand and model format.

Closely related to the modelling methodology is the analytical approach supported by a tool. The analytical approach refers to the assumptions about the constitution of the models prior to creating the models. There are two analytical approaches; top-down and bottom-up. In top-down approaches, the model is concerned with economic and social processes in which an energy system is embedded, whereas bottom-up approaches model the technical operation of the energy system. Therefore, technology is modelled as an aggregated black-box in top-down approaches, but in detail in a bottom-up approach. Top-down approach is also known as the economic paradigm whereas bottom-up approach is the engineering paradigm [66]. Phase II of the CEP analyse operations of the energy system using bottom-up approach, while top-down approach could situate or integrate the energy system within a socio-economic context.

Whilst bottom-up models are used for economic and environmental impact assessment, they are not considered top-down approaches because the economic and environmental processes are not modelled, instead only the techno-operational process is modelled. The economic and environmental variables used for the assessment are calculated directly from the outcome of the operations of the energy system. Unsurprisingly, all the (groups of) energy software discussed are bottom-up approach, though some are hybrid because they include top-down approach. However, Generic Software should be able to model both top-down and bottom-up approaches.

Supply-demand dimension refers to whether the software models the supply-side or demand-side or both. Supply-side refers to availability of energy (including energy storage) and the relevant issues include availability of energy on demand, efficiency (technical performance), and impact (e.g. social, economic and environmental). Demand-side refers to use of energy and the relevant issues include cost of energy and time of energy use. Energy demand is an exogenous variable in supply-side models, while energy supply is exogenous in demand-side models.

Among the tools reviewed, there appears to be a relationship between analytical approach and the supply-demand dimensions. Bottom-up approach is only applied on supply-side models where demand is an exogenous variable. Top-down approach is applied to both supply-side and demand-side.

Model format refers to whether the model can be presented as a graphic or text or both; and it should not be confused with modelling interface (most tools have both text and graphic interfaces). This dimension has not been considered in past classifications, but it has implications on the transparency of the model. Some energy software have a graphical and text format, while others have only text. Similarly, some Generic Software have only text format. Having a graphical and text format allows to present the model in layers, requiring different expertise to read: a graphical format may be self-explanatory or may require little instruction; a text format typically requires more expertise. The more readable a model is, the more transparent it is, and transparency is important in participatory processes where stakeholders are from different backgrounds.

2.4.4.9 *Conclusion: Limitations and Comparison*

Previous sections have focused on the strengths of the various modelling tools. Energy software have the following limitations (in comparison to Generic Software): offers less creative flexibility to the creator; limits the level of transparency on created models especially regarding internal assumptions on endogenous relationships between variables; each software has its self-contained proprietary 'language' which is made easier to use via GUI; all software considered support bottom-up approach but there are few hybrids of top-down and bottom-up; integration with other tools are less likely or low due to proprietary formats (whereas if that is the case with Generic Software, all models can be made in the same tool); and there are no demand-side software for a bottom-up approach. Regarding transparency, whilst most energy software have extensive reporting capabilities which may be easy for stakeholders of different backgrounds to understand, reports communicate analyses generated from the models, but transparency is concerned with the structure of the models.

Whilst the more flexible programming-based Generic Software like MATLAB and Python may be able to address the limitations of energy software, a major limitation is the lack of a graphical format of the model. Therefore programming-based generic software create text-based models only, which requires higher level of expertise to understand and are not readily visualised. On the other hand, other Generic Software have both graphic and text formats. SD software like Vensim, iThink and AnyLogic offer both formats, but unlike Generic Software, the SD software have the same (standardised) graphical representation because they use SD graphical nomenclature in terms of Stock and Flow Diagram (SFD) and Causal Loop Diagram (CLD). Moreover, many other systems methodologies use CLD to visualise mental models. Therefore, SD Generic Software combines two strengths from energy software and Generic Software which enhances its transparency. Transparency is improved by having a graphical format like energy software, but also transparency from not having assumptions about the models embedded in the modelling software, as a Generic Software.

2.4.5 Phase III: Multiple Criteria Decision Analysis

2.4.5.1 *Introduction*

MCDA has been mentioned in several previous sections as part of the CEP methodology, and as combined with PSM. This section on Phase III goes into more detail. Unlike the discussions in Phase I and Phase II which go in-depth to the methodologies and tools, the discussion in Phase III will be broad, although the methodologies will be discussed briefly. This is because the thesis aim is focused on SD, and therefore, the issues of MCDA covered would focus on some the themes of this chapter (which include processes and methodologies) and issues relevant to the interaction between MCDA and SD.

2.4.5.2 *What is MCDA?*

Multiple Criteria Decision Analysis (MCDA), also known as Multiple Criteria Decision-Making (MCDM) is a branch of Operational Research (OR) [175], [176], as well as a tool [175], with rational foundations in other disciplines [177]. MCDA is used in place of MCDM to highlight that the methods aid decision-making, but are not the decisions themselves [178]. MCDA is also a generic term for methods with the two characteristics: aid decision-making according to preferences of stakeholders [178], [179]; have more than one criterion, with possible conflict among them [176], [179]–[181]. Furthermore, the same MCDA method may be used in different scope as 'comprehensive' or ‘composite’ methods [182] e.g. Analytic Hierarchy Process (AHP) can be regarded as a comprehensive MCDA method, as well as a weighting method.

MCDA analyses products, services or policies [181] and actions [183]. MCDA problems have four features [175], [182]: goals; preferences or priority; alternatives; and criteria or indicators. Alternatives can be expressed as discrete or continuous variables. It seems discrete alternatives are defined by criteria of interest, whereas continuous alternatives are defined by constraints. Furthermore, the outcome of MCDA depends on factors like the method of ranking alternatives [184], MCDA method of choice [185], [186], person applying the method [78], and variability (uncertainty) of criteria values [184].

There are many applications of MCDA in fields that are related to CEP. A review of 196 studies [187] found about 90% of MCDA applications in areas like Environment Impact Assessment, energy management, sustainability assessment, renewable energy, waste management, climate change, etc. In another review study [176], about 70% of MCDA applications were identified in areas like Renewable Energy Planning, project utility planning, energy resource allocation, Building Energy Management, project planning, etc. Review studies have confirmed that MCDA can aid in making decisions that affect the (natural) environment especially under uncertainties [187], as well as in energy management (planning) [188]. MCDA has been presented by some review studies in terms of its application as a decision support system (DSS) [189], as a strategy to green energy problems [188], and as a method of conducting SA [181].

MCDA can also be used to seek the most suitable SA methods as well as to aggregate Sustainability Indicators (SI) into a General Sustainability Indicator [123]. More generally, MCDA methods are beneficial for their ability to facilitate the following [175], [176], [181], [187]: negotiation or compromise; quantification of importance/values; communication and transparency; participation of stakeholders; structure or systematisation; reliability of the process. However, as shall be discussed, MCDA is fraught with challenges in achieving these benefits.

2.4.5.3 *MCDA Process and Methods*

Based on [120], [178], [182], [187], MCDA procedure can be understood as having four stages in the broad sense: input collection; problem formulation/structuring/weighting; problem processing/evaluation/aggregation; interpretation of results. In the narrow sense, where all the studies agree, MCDA is the second and third stages only.

Two descriptive frameworks have been used to categorise MCDA methods. One framework has three dimensions [175] while the other has four dimensions [176]. The three-dimension framework includes: type of alternatives; 'Modelling' approach; direct or indirect approach. The four-dimension framework includes: type of alternatives; modelling approach; deterministic or stochastic or fuzzy; single DM (decision-maker) vs group DM. Type of alternatives refers to whether the alternatives are discrete or continuous variables; those with discrete alternatives are considered Multi-Attribute Decision Making (MADM) methods, whereas those with continuous alternatives are considered Multi-Objectives Decision Making (MODM). Modelling approach refers to the means of determining which alternatives are prioritised. Examples of approaches include value measurement, outranking models, distance-based models etc. Examples of modelling approaches and the classifications are provided in Table 4 based on [50], [123], [175], [176], [178], [181], [182]. Modelling approach is a useful dimension to categorise the methods because this work is interested in methodology. Therefore, the other dimensions will not be discussed further.

Reference	Method Category		Methods
[50]	MADM	Value Measuring	AHP and MAUT
		Goal Programming	TOPSIS and STEP
		Outranking	ELECTRE and PROMETHEE
[178]	MODM		
		Value measurement model	AHP and MAUT
		Goal, aspiration and reference-level	TOPSIS and STEP
		Outranking	ELECTRE and PROMETHEE
		Combination	-
[175]	MCDM Models	Utility Based	AHP and MAUT
		Outranking	ELECTRE and PROMETHEE
		Miscellaneous	NAIADE
[176]	MCDM	Priority based	-
		Distance based	TOPSIS and STEP
		Outranking	ELECTRE and PROMETHEE
		Mixed methods	-
[181]	MCDA Methods	Utility function	AHP and MAUT
		Outranking relations	ELECTRE and PROMETHEE
		Sets of decision rules	DRSA
[123]	MCDM Category / Distance functions		TOPSIS

		Discrete methods	Outranking	ELECTRE and PROMETHEE
			Hierarchical	AHP
			Ranking and Classification	DRSA
			Optimising averages	MAUT
[182]	MCDA Methods		Elementary	-
			Unique synthesizing criteria methods Fuzzy methodology	AHP and MAUT TOPSIS
			Outranking	ELECTRE and PROMETHEE
			Others	NAIADE

Table 4 – MCDA Methods Categorisation

2.4.5.4 *Issues in MCDA*

As mentioned earlier, the benefits of MCDA are undermined by some challenges. Some of the issues in MCDA include validity, choice of MCDA method, complexity, uncertainty, criteria for selecting MCDA methods, criteria within MCDA methods. These issues shall be discussed below.

2.4.5.4.1 Validity

The validity of MCDA to a decision-maker is confidence in the decision that is arrived at via MCDA [178], [187]; by decreasing post-decision regret [179] and accounting for all significant criteria [187]. In other words, decision-making is made explicit, rational and efficient [176], [187]. Therefore, MCDA systematises the decision-making process which enables transparency and reproducibility. Furthermore, MCDA methods should reflect the 'true values' of the stakeholders [187]. After all, preferences of a decision-maker are the primary determinant of the MCDA method of choice [178] [181], [189]. However, different MCDA methods applied to the same problem can lead to different recommendations [178], as well as when applied to the same objectives, can also lead to different recommendations at different times [175], which are all valid. Which method is more 'valid' depends on the decision-maker.

2.4.5.4.2 Choice of Method

The choice of appropriate MCDA method is itself an MCDA problem [178], [189]. Since it cannot be said that one MCDA approach is better than another [123], [178], [190], then the choice of the most suitable MCDA method depends on the characteristics of the problem; like the number of criteria, indicators or stakeholders [123]. Each problem would seek the strengths of multiple methods, leveraging on their strengths [123], [178], [191] and avoiding their weaknesses [175]. Moreover, MCDA outcomes are affected by choice of methods, but affected more by change of methods [185], [186].

Having noted that some MCDA methods like AHP are applied as comprehensive MCDA methods or as weighting methods [182], this provides a new dimension to multi-method MCDA because not only could it mean multiple comprehensive MCDA methods, but also a single (or more) solution made from a combination of composite methods that form stages of the MCDA process (to the extent that they are compatible).

The criteria for the selection of MCDA methods are validity, suitability, understandability and feasibility[178], [186], [187]. Validity refers to whether the method measures what is supposed to be measured. Suitability refers to the compatibility between the method and available information, or ability of the method to process available information. Understandability refers to ease of understanding, or user-friendliness, or simplicity, while feasibility refers to feasibility of outcome. However, many MCDA studies do not justify their choice of methods over others [123], and they are driven by subjective preferences [181]. This also means researchers may not be aware of the limits and theoretical foundations of the chosen methods despite familiarity with the procedure [123].

2.4.5.4.3 Complexity

Complexity in MCDA can be understood from two perspectives: complexity of information required to make decisions; and complexity of alternatives. The sources of complexity for decision-making information includes heterogeneity of information sources that could justify contradictory sources of action, uncertainty from insufficient information required for managing risk, and subjective weighting of alternatives [175], [184], [187]. In the case of alternatives, the sources of complexity include variety of criteria, conflicting objectives, and multiple stakeholders [175]. To deal with the complexity of information, the MCDA process should rely on expert judgement and a systematic framework to organise technical information [187].

2.4.5.4.4 Uncertainty

Some of the uncertainty in MCDA come from stochastic input information, criteria weights and preference function parameters, inconsistent criteria units, and the geographical scale of the problem (the larger, the more uncertain) [184], [187]. Some ways to deal with uncertainty in MCDA includes: sensitivity analysis [192]–[195], scenario analysis [190], [192]–[194], using multiple MCDA methods for robustness [176], [185], [186], [196], Monte-Carlo Simulation [184], [196], [197], distance-based analyses [198], review of decision-makers weights/priorities by interview and discussions [185], [186], interactive decision support system [176], and setting thresholds of preference and indifference [181].

2.4.5.4.5 Criteria within MCDA Methods

Within the context of EP, five principles were provided for selecting major criteria in an MCDA process [182]: systemic principle; consistency principle; independency principle; measurability principle; comparability principle. For systemic principle, the criteria system should be more than the sum of the individual criteria. For consistency principle, the criteria system should be consistent with the decision-maker's goal. For the independency principle, there should not be overlap in the dimensions the criteria measure. For the measurability principle, the criteria should be quantifiable; qualitative or quantitative. For the comparability principle, the criteria should be normalised such that results of MCDA are obvious.

With regard to the independency principle, it has been noted that MCDA literature lacks consideration for interdependence [184] (for example, how "impacts on amenity and the costs of the technology will affect the public's acceptance of a certain technology"). It was suggested that Monte-Carlo Simulation would be able to deal with the issue of independency principle [184]. Instead of the listed principles, rational methods (like Delphi method, LMS, Minmax deviation) of selecting criteria for EP problems can be used [182]. The most popular criteria in EP according to review studies are technical efficiency, investment cost, CO_2 emission, and job creation [120], [182].

Within the context of Sustainability Assessment (SA), seven principles for selecting SA criteria [120], which could be applied to MCDA, should cover all aspects of sustainability, but should not overlap. Furthermore, [181] presents 10 crucial criteria of SA tools which MCDA methods should be subjected to before using for SA. The 10 criteria are grouped into three: scientific soundness; feasibility and utility. Scientific soundness includes: use of qualitative and quantitative data; life cycle perspective; weights typology; threshold values; compensation degree; uncertainty treatment or sensitivity analysis; robustness. Feasibility includes: software support and graphical representation; ease of use. Utility includes: learning dimension.

2.4.5.4.6 Criteria and the Issue of Weight and Trade-off

A criterion in an MCDA problem is only as influential as the importance assigned to it, which is its weight. Weighting is a major source of complexity [175], and hence a challenge. Factors that are considered when determining the weight of a criteria are the subjective preference of decision-makers, variance degree of criteria, and independence of criteria [182].

MCDA applications have been criticised for misuse of weights by eliciting them as importance coefficients rather than trade-offs [181]; the implication being the difference between a more reductionist and a more holistic approach respectively, because when presented as a trade-off, a criterion's value is also a statement to the value of other criteria, not independent. Furthermore, there is concern about the lack of relativity among weights which can be achieved by bounding them to criteria ranges [199].

2.4.5.5 *Conclusion: Problem Structuring*

Problem definition is not incorporated into the procedures of MCDA; also lacking are Stakeholder Analysis, development of alternatives and exploration of uncertainty [30]. This increases the risk of recommending the ‘wrong solution’ and solving the ‘wrong problem’. In addition, the very general questions used to elicit weights (priority) of criteria in MCDA lack interpretation of the context within the MCDA method. PSM were developed to address complex problems that are ill-structured in Operational Research (OR), where MCDA is most practiced [200]. PSM has been discussed in more detail in Section 2.4.3. In a review article [30], 68 articles that cover application of combined PSM-MCDA to problems were reviewed. Based on the above, it could be said that MCDA is too ‘hard’ as a method, because it lacks ‘softness’.

All the issues of MCDA discussed can be addressed significantly by PSM; the issues are validity, choice of MCDA method, complexity, uncertainty, and choice of criteria and weighting. The following are some of the aspects of the issues that PSM can address. First, validity to the user ultimately depends on the user especially because different MCDA methods lead to different recommendations on the same problem. Second, the choice of MCDA method should depend on validity, suitability, understandability and feasibility. Third, the sources of complexity in MCDA include heterogeneity of information sources that could justify different recommendations, and subjective weighting. Fourth, variance in weighting of criteria leads to uncertainty. Fifth, the choice of criteria and weighting (and resulting trade-offs) depend on subjective, and often from multiple, perspectives. In summary, the issues can be summarised as subjectivity in preferences, and difference in understanding of the problem. As mentioned earlier, PSM aims to achieve clarity, resolve conflicts, and possibly even some level of consensus prior to seeking solutions to the problem [139].

2.4.6 Conclusion on CEP

CEP has been defined and the phases of CEP have been discussed in terms of their aims and the groups of methods utilised in the phases. Furthermore, the methodologies and tools in Phase I and Phase II were discussed in-depth, whereas Phase III was explored more broadly. In Phase I, it was argued that SD is a suitable PSM. In Phase II, it was argued that SD could be used to carry out analyses of mathematical modelling tools, while highlighting its strengths and limitations. In Phase III, MCDA was discussed and shown to require combination with PSM to avoid problems that can undermine the benefits of the method, especially in problems with multiple participants as expected in CEP.

So far in this chapter, SA and CEP have been discussed. The thesis aim has been addressed: to explore the methodologies used in CEP which facilitate participation from multiple stakeholders. To address another thesis aim, which is to explore SA for CEP, two steps will be taken as mentioned in the chapter's introduction. The first step has been addressed which is to discuss SA in general. The second step is to argue that CEP incorporates SA, which will be discussed in the next section. Subsequently, the chapter will conclude with two sections addressing the third thesis aim which is to propose a SD-centred methodology for CEP, and identify gaps in the literature that demonstrate SD in the constituent methods.

2.5 CEP as SA

Having looked at SA and CEP, this section makes the case for why the CEP can be considered a form of SA. Since SA is assessment using SI, and CEP also involves assessment of energy systems using SI, CEP can include SA or may even be considered a form of SA. The relevance to the thesis is that the research question is interested in sustainable CEP, not just CEP. The implication is that the indicators used in CEP would include SIs but not limited to SIs.

SA has been used for Energy Planning at community-level in [104], [113], [119], [122], [201], [202], where the projects and plans were assessed using SI. CEP can be understood as a form of SA, or at least having many parallels with SA which include: their definitions; use of SI; process; trade-offs; and integratedness. From the definitions of SA and CEP, they intersect on sustainability. SA evaluates sustainability using SI, and CEP also evaluates sustainability using SI in analyses carried out by mathematical models, while aiming for sustainability. Many SI can be defined and utilised in Phase I, Phase II and Phase III of CEP. Simple SI were combined into composite SI using MCDA in EP [118], [123], which parallels CEP where criteria are defined in Phase I and aggregated in Phase III using MCDA. Furthermore, the SA processes outlined in [93], [95], [124] (Table 2) align with the CEP process in the same sequence (Figure 5).

The descriptive and prescriptive frameworks of SA also align with CEP. All three categories of SA tools in [121] (indicators, product related methods and integrated assessments) are utilised in CEP e.g. CO_2 emissions, LCA, SD and MCDA respectively. The three categories of tools in [86] (decision support; bio-physical, economic and social tools; integrated tools) are also utilised in CEP e.g. MCDA, SD and LCA respectively. Moreover, the seven dimensions of SA in [86] are all important issues in CEP, and these are: boundary-orientedness; comprehensiveness; integratedness; stakeholder's engagement; scalability; strategicness; and transparency. Comprehensiveness and integratedness are also relevant to the research questions of this work.

Other SA issues discussed – trade-off and integratedness – are also important in CEP. Phase I of CEP is especially concerned with trade-off in the form of conflict management and building consensus, but all the first three phases may deal with trade-off because of the multiple stakeholders involved. Based on the levels of integration in SA from [93] and [89], this work is primarily concerned with integration of methods by seeking a comprehensive methodology that spans multiple methods and phases. However, CEP is also concerned with integration of themes by focusing on sustainability which includes several concerns, and integration of processes by allowing feedback of processes across phases. Finally, the move towards a holistic sustainability science also aligns with the participatory and transdisciplinary aspirations of

CEP. Based on the above, CEP can be regarded as a form of SA, or SA can be considered to be embedded in CEP.

2.6 Proposed Methodology for CEP

Given the wide methodological scope of SD in Section 2.4, System Dynamics (SD) can perform many methods in CEP. In Phase I, SD encompasses PSM (Section 2.4.3) which are more suitable and comprehensive than organisational management methods like SWOT and SMART (Section 2.4.2). In Phase II, SD has been used for simulation and optimisation via simulation (Section 2.4.4). In Phase III, MCDA integrates well with, and is significantly enhanced by, PSM (Sections 2.4.3 and 2.4.5.5). Therefore, the proposed methodology is centred around SD as illustrated in Figure 8 which is based on Figure 6 (original methods stack). Given the scope of SD in the different phases of the CEP methodology, SD is comprehensive in the methodology.

The benefits of the methodology include ease of integration, transparency and synergy. The methodology facilitates integration between methods and across phases, and consequently integration between activities, due to the common modelling language of SD used in the different phases. Additionally, transparency is facilitated due to the common language, and consequently participation is facilitated. Furthermore, the methodology benefits from synergy between phases and methods. For example, between phases, the mental models generated from Phase I can be developed into top-down simulation models in Phase II, whereas between methods, problem structuring from Phase I can be used to prioritise MCDA choices in Phase III.

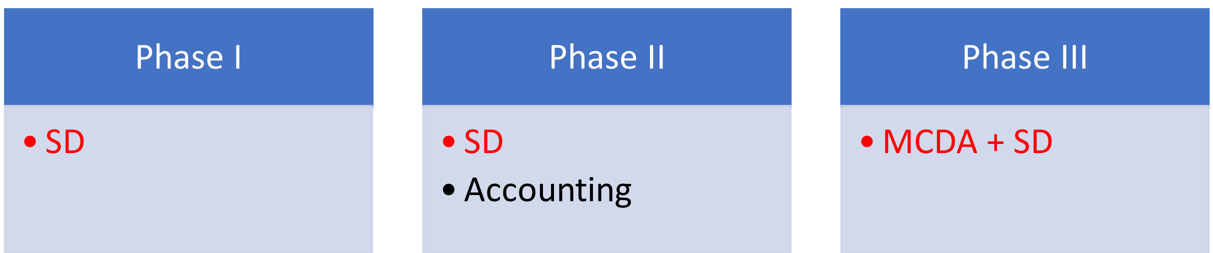

Figure 8 – Proposed CEP methodology utilising SD

2.7 Gaps in the Proposed Methodology

There are gaps in the demonstration of the proposed CEP methodology. Since the use of SD in Phase I and III are as mental models, demonstration of their use in CEP specifically is not necessary, because mental models are conceptual or cognitive [34]; it is sufficient that they have been demonstrated in other fields. However, SD must be shown to be demonstrated in CEP for Phase II, because mathematical models must have valid equations that may be peculiar to different fields.

Looking at the proposed methodology in Figure 8, Phase II has three categories of mathematical models which are optimisation, simulation and accounting. SD is not an accounting methodology even though accounting modelling is technically possible on any Generic Software that can execute equations. Whilst SD is a simulation methodology, it can also be used for simulation-based optimisation to find the set of configuration with the most desirable outcome within a specified search space (Section 2.4.4.2). Given the categorisation of simulation into top-down and bottom-up approaches (Section 2.4.4.8), all the SD models found in EP literature are top-down approaches modelling the energy industry [60]–[65], [203] and community-level projects that interact with CEPs [60]–[62]. However, there has been no attempt found on bottom-up models of energy systems using SD.

There is another way to look at the gap in SD demonstration using the grid of problem context from [34] (see Figure 1). The modelling methodologies in Phase I and Phase II can be located as in Figure 9. SD can be utilised for simple and complex problems with unitary and pluralist participant relationships. However, only the simple-unitary problem context – which characterises bottom-up simulation – is yet to be demonstrated by SD. Therefore, bottom-up models using SD is the gap that subsequent case-study chapters will attempt to demonstrate.

		Participants		
		Unitary	Pluralist	Coercive
Complexity	Simple	Phase II: Bottom-Up Simulation	Phase I	-
	Complex	Phase II: Top-down Simulation		-

Figure 9 – Placing the methodologies of the CEP Phases in the grid of problem context

2.8 Conclusion

This chapter has addressed three thesis aims but only two thesis objectives. The first aim is to explore SA for CEP which has been covered in sections 2.2 and 2.5. The second aim has been addressed in Section 2.4, which is to explore the methodologies used in CEP which facilitate participation from multiple stakeholders. The third aim is to propose a SD-centred methodology for CEP, and identify gaps in the demonstration of SD within the proposed methodology, which have been done in sections 2.6 and 2.7. The justification for the choice of SD as the central methodology had been made in sections 1.1 and 1.2, but the details of the wide scope of SD has been provided in sections 2.4.3, 2.4.4 and 2.4.5. The yet unaddressed thesis aim, which corresponds to thesis objectives 3-8, will be addressed in the remainder of the thesis (chapters 4-9). Before then, the methodology that is shared among the case-study chapters will be discussed in Chapter 3.

3 Methodology

3.1 Introduction

This chapter covers the part of the methodology that is shared by the case-study chapters. There are two parts to the shared methodology: the SD modelling process for bottom-up simulation; and framework for SA. Therefore, the methodology section in each case-study chapter does not repeat the details of what will be covered in this chapter.

3.2 System Dynamics

This section focuses on parts of SD that are relevant to the methodologies of the case-studies. Therefore, the following focuses on SD as applicable in bottom-up simulation or simple-unitary problem context (see Figure 9).

3.2.1 Modelling Process

Equivalent processes of SD have been outlined in [72], [77]–[79]. The process used in this study is an adaptation of the modelling stages in [77] and [72], as illustrated in the flowchart in Figure 10, which also shows the associated input and output to the stages, as well as relevant validity tests for the stages. There are three modelling stages: Problem Articulation; Model Conception; Model Formulation. For each stage, there are inputs and outputs, and validity tests on the outputs which lead to revision of the stage's output if unsatisfactory. At the end of the successful modelling process, the output is a valid model. Subsequently, analyses can be carried out with the valid models.

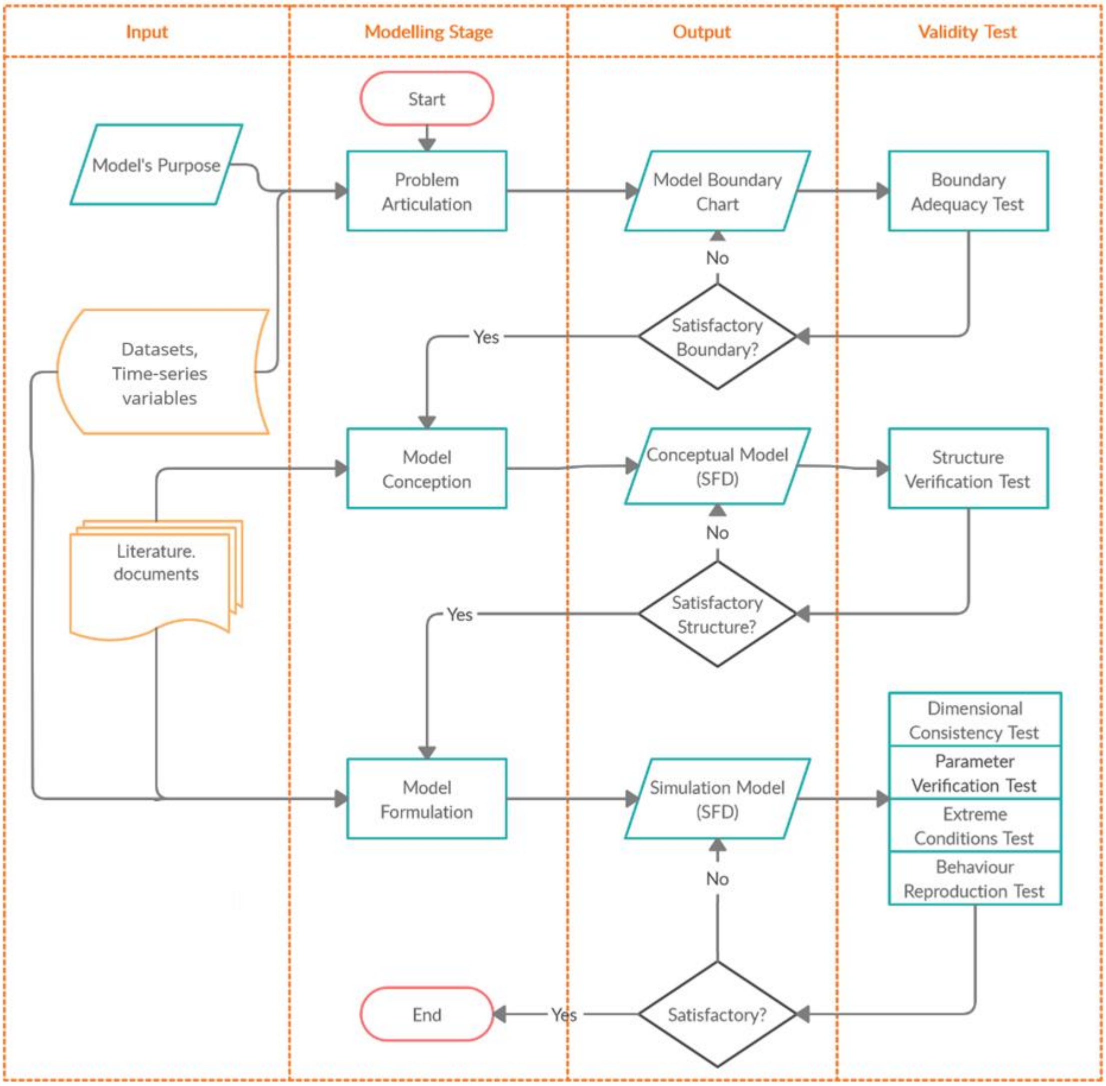

Figure 10 – Flowchart of the SD modelling process

There are conceptual tools for the three modelling stages. The tool used in problem articulation is a Model Boundary Chart (MBC), while Causal Loop Diagram (CLD) and Stock and Flow Diagram (SFD) are used for Model Conception, and only SFD is used for Model Formulation. A MBC defines the model's boundary in terms of the major variables that are to be included in the model and those that have been deliberately excluded. The included variables are separated into endogenous and exogenous variables; MBC is typically presented as a table with three columns for endogenous, exogenous and excluded variables. Having as many endogenous variables as possible improves the chances of understanding and insight into the real system being modelled. For the next two stages that use CLD (Section 2.2.3) and SFD (Section 2.2.4), the software used is Vensim PLE+ for Windows Version 8.0.9.

Whilst each case-study provides the context for selection of system components, the case-studies can be divided into two: those focused on validation (chapter 4 and 6) and those focused on decision-making (chapter 5, 7 and 8). When focused on validation, the system components are selected to be comparable to the system it would be validated against; e.g. similar appliances should be in the modelled 2-occupants residence as found in the compared 2-occupant residence. When focused on decision-making, the system components are selected to facilitate answering the research questions; more detail is provided in Section 3.3.

3.2.2 Validity and Validity Tests

For every real system, there can be several valid models [72]. However, based on the confidence they exert, they are not all equally valid. Therefore, as long as a model is not invalid, the degree of validity is subjective to the user or community of users [73]. A model is successful if it fulfils its purpose [74], which in the case of bottom-up SD is to allow for virtual experiments and what-if explorations .

Validity tests have been developed in SD literature to systematically interrogate the validity of the modelling process and intermediary outputs, rather than focusing on the final output only. Validity tests are necessary for the validity of a model [75]. Validity tests should be holistic, engaging all model variables and their relationships. Two groups of validity tests are the minimum requirement for validity: model structure tests; and model behaviour tests [75]. Model structure tests evaluate how realistic the structure of the model is; every model element should have a real world, and every important factor in the real system should be captured in the model. Model behaviour tests evaluate how realistic the behaviour of the model is given a variety of parameter values. These tests make the process of SD rigorous on model variables which improves the confidence; making them reasonable and consistent with reality [75].

The validity tests in Figure 10 were adapted from [72], [75], [204]. Each validity test can be expressed as questions whose responses would lead to positive validity results [72], as shown in Table 5. The aim of the validity tests is to impart confidence on the user of the model.

Validity Test	**Questions to ask**	**Positive Validity Result**
Boundary Adequacy	• Is the model boundary appropriate to the purpose? • Are the important concepts for addressing the problem endogenous to the model?	All major variables are relevant to the purpose. Major variables are endogenous; as much as possible.

Structure Verification	• Is the model structure consistent with relevant descriptive knowledge of the system? • Is the level of aggregation appropriate? • Does the model conform to basic physical laws such as conservation laws, or contradict common sense? • Do the decision rules capture the behaviour of the actors in the system?	A SFD justified by the data sources or/and sound reasoning.
Dimensional Consistency	• Is each equation dimensionally consistent without the use of parameters having no real world meaning?	Units of variables are consistent and balanced throughout the system. Units should also be meaningful. Choice of units is appropriate and justified.
Parameter Verification	• Are the parameter values consistent with relevant descriptive and numerical knowledge of the system? • Do all parameters have real world counterparts?	Parameters are realistic to the system, and justified by data.
Extreme Conditions	• Does each equation make sense even when its inputs take on extreme values? • Does the model respond plausibly when subjected to extreme parameters?	That behaviour in extreme condition matches anticipated or historical behaviour. Model is robust by behaving realistically to the input.
Behaviour Reproduction	• Does the model reproduce the behaviour of interest in the system (qualitatively and/or quantitatively)?	Minimal error/deviation from historical or expected behaviour.

Table 5 – Questions for validity tests and expected positive validity result

3.3 Framework for Sustainability Assessment

At the end of a successful modelling process, a valid simulation model is ready for analyses. The main analysis used in the case-studies is scenario analysis. Scenario analysis defines configurations of the system, also known as scenarios, then quantifies, and possibly compares, the performance of the scenarios. Scenarios are defined by the system's exogenous variables and other parameters used to calculate the performance of the scenarios. Figure 11 visualises a proposed conceptual framework to be used to aid in the design of sustainability assessment studies that are based on simulation models and scenario analysis. The framework can also be used to describe such studies, and it is agnostic of the simulation tools chosen. The SA framework was created based on literature on performance assessment of RES in Chapter 5, and it will be implemented in Chapter 5, Chapter 7 and Chapter 8. Only a general operational overview is provided in this Chapter on how to use the framework to describe designed studies.

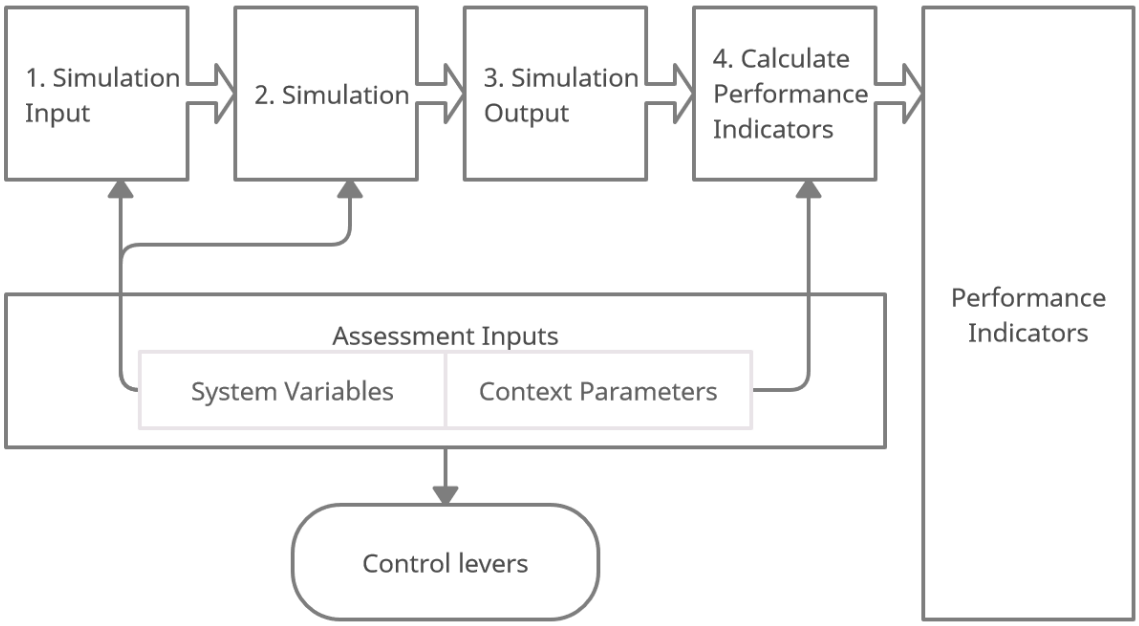

Figure 11 – Proposed framework for describing and designing performance assessment studies of energy systems based on simulations; showing the design of this study as an example.

There are two mathematical processes in the proposed SA framework illustrated in Figure 11: simulation; and calculation of Performance Indicators. The shapes with sharp edges and arrow heads represent stages in the mathematical process. Numbered one to four, the first three are simulation stages, while the fourth is calculation of Performance Indicators. The Performance Indicators are calculated using output from the simulation and Context Parameters, and may be calculated at the end of the simulation or concurrently. Sharp rectangles represent all variables that are either input or output to the mathematical process; Assessment Inputs are input, while Performance Indicators are output. The rounded rectangle is the Control Levers, which is a subset of the Assessment Inputs.

Assessment Inputs is a set that contains all possible input to the simulation model, which includes system variables, and context parameters; note that there is no input from Assessment Inputs to Simulation Output. Therefore, Assessment Inputs is divided into System Variables and Context Parameters. System Variables include exogenous and endogenous variables of the modelled system, where exogenous variables are constants including time-series that may serve as input to the simulation, while endogenous variables refer to mathematical description of components in the modelled system. On the other hand, Context Parameters are variables that describe the assessment context of the modelled system; for example economic parameters like discount rate, and environmental parameters like emission factor.

Performance Indicators quantify the performance of the modelled system technically, economically or environmentally. The input to the calculation of Performance Indicators are the simulation's output and context parameters. In other words, Performance Indicators are the sustainability indicators of a bottom-up simulation model; the social dimension of sustainability is typically captured in top-down simulations. Control Levers, being a subset of Assessment Inputs , refer to those Assessment Inputs which the researcher is interested in varying (based on their research questions or aims) to find out their impact on Performance Indicators. Typically, Control Levers define simulation scenarios.

To design a study using the framework, there are two steps: define the purpose of the study; and identify required variables. After the design, the next task is to run the simulation model and calculate Performance Indicators. In the first step, the purpose of the study is specified in terms of Control Levers and Performance Indicators. The purpose is defined in more detail as scenarios by specifying which Control Levers and Performance Indicators define each scenario. Therefore, a study without variables in Control Levers and Performance Indicators is purposeless. In the second step, Assessment Inputs is used to identify the required variables to achieve the purpose of the study by taking stock of the availability of the system's inputs (exogenous variables), the modeller's capability to model the system components (endogenous variables), the equations of the Performance Indicators, as well as the availability of parameters required to calculate the Performance Indicators. Therefore, the second step is essentially expressing all variables as constants or equations. As a validation check, Assessment Inputs must contain all the Control Levers. Instead of listing all the many Systems Variables of a model in Assessment Inputs, the few that are considered key to understanding the study can be listed, to aid readability.

The SD model building process discussed in Section 3.2.1 entails the two steps of the SA framework, but while the SA framework takes a wider look at the research problem, the modelling process takes a deeper look in terms of details in the second step of the study design. The wider look provided by the SA framework is the inclusion of Context Parameters, and the calculation of Performance Indicators. Therefore, the SA framework should be used to design and describe a study prior to commencing the model building process. Whilst the SD simulation can accommodate both Context Parameters and Performance Indicators as part of the modelled system, typical simulation methods would simulate a system's operation first and then assess the performance of the system afterwards, not concurrently. After all, the framework is intended to be used with any simulation method, and so the lowest common denominator is considered. Furthermore, the SA framework succinctly describes the design of a study.

The case-studies that implement the SA framework mainly utilise scenario analysis, although sensitivity analysis could be described by the framework. This is because the aims of the case-studies (which are based on the thesis objectives) that involve decision-making analysis (chapters 5, 7 and 8) are more concerned with making a choice between scenarios, than on understanding the contribution to uncertainty of endogenous system variables (outputs) by exogenous system variables (inputs), which is what sensitivity analysis aims to evaluate [205]. Moreover, sensitivity analysis is especially suitable for systems where the relationship between the model's endogenous and endogenous variables is not well understood which leads to high uncertainty [205]. These are basically dynamically complex systems (see Section **Error! Reference source not found.**) which are difficult to understand by humans, even with computer models, and lead to high uncertainty [72]. Whilst the model used in Chapter 7 may be considered dynamically complex, the models in Chapter 5 and Chapter 8 are not dynamically complex. Nonetheless, in the models used in all three chapters, the endogenous variables are discrete, which leads to discontinuity on the one hand, but also predictability of the limits of the effects that an exogenous variable could have on the endogenous variables.

The framework lacks low resolution details like the simulation method used, or how the control levers are varied. Therefore, two studies may be described identically using the framework but may use different simulation methods or have different research objectives. Also, this does not preclude having non-identical descriptions of studies which have the same research objectives, but go about addressing it using different variables. However, it structures the design of a study and can be used to describe a study succinctly. Therefore, an explanation should accompany the illustration of the study design.

3.4 Secondary Data

Multiple secondary data have been collected or generated to be used in the case-study chapters. These can be grouped into three: residential load collected from real residences; residential load generated from simulated residences; and simulation parameters used in simulated residences. From real residences, Chapter 4 uses residential load from Project SENSIBLE (Storage Enabled Sustainable Energy for Buildings and Communities) [206] for validation, while Chapter 6 is validated using residential load from the UKDA (UK Data Archive 6385) dataset [207]. From simulated residences, Chapter 5 uses load generated from the CREST (Centre for Renewable Energy Systems Technology) Demand Model of the University of Loughborough [208] as input to the created supply model, while Chapter 6 uses load from the CREST model to validate the created model. Furthermore, some parameters from the CREST model were used as parameters for the models in chapters 6 and 8. Finally, parameters used in the case-studies are obtained from the UK context, as the case-studies are situated in the UK. The details of the specific data used will be explained in the relevant chapters.

3.5 Conclusion

This chapter discussed the SD modelling process and related concepts like feedback, validity and modelling language. Furthermore, a SA framework for simulation models was proposed and discussed. Having addressed some of the thesis aims and objectives in Chapter 2, subsequent chapters will utilise the methodology discussed in this chapter to address the remaining thesis aims and objectives. Chapters 4, 6 and 7 make use of the modelling process, while chapters 5, 7 and 8 make use of the SA framework.

4 Supply-side SD Models from the Bottom-up

4.1 Introduction

This chapter is the first case-study chapter on which some of the subsequent case-studies build on. The aim of the chapter is to create a valid bottom-up supply-side SD model, which is the third thesis objective. The SD model created is of a RES, but supply-side models of individual RES were not found in the literature. Therefore, a brief survey of bottom-up supply-side models of RES microgrids is provided, highlighting some gaps in the literature that a SD model would be able to contribute towards. However, the main value of a SD approach in this thesis is in demonstrating the applications of SD in the comprehensive methodology for CEP that was proposed in Chapter 2. In addition to discussing the modelling process which is based on Chapter 3, SD concepts are mapped to components of energy systems.

The models are created and validated using data from project SENSIBLE [206] in Nottingham, UK. The models feature energy conservation, energy conversion loss based on a non-linear efficiency curve, and causal connectedness.

4.2 Literature Review

EP is a complex process involving many problem areas, activities and participants. This necessitates inter-disciplinary or even trans-disciplinary approaches to the problems. Modelling the operations of energy systems is essential in EP at different scales, e.g. communities and cities [51], [54]. Based on the review in [54], at the heart of bottom-up EP are techno-economic assessments, techno-ecological assessments and what-if analyses, and all these rely on a model of the operations of an energy system; what-if analysis includes scenario, sensitivity and optimisation analyses.

Energy software based on SD are rare. Among the 96 energy software reviewed in [138], only one is based on SD: UniSyD3.0 which is a top-down approach and partial equilibrium model [209]. Beyond energy software, many models in EP literature are based on generic tools or methods. In a 2017 comprehensive review of Generation Expansion Planning looking at over a hundred papers [49], only four used SD: [64], [65], [203], [210]. Integrated into a larger model as sub-models, SD was used in [60]–[62], as reviewed in [51]. All the mentioned applications of SD to EP problems are top-down approaches. Therefore, there is a gap in the literature of review studies for bottom-up approaches using SD.

Beyond review studies, a survey of bottom-up supply-side models of RES microgrids was carried out. Some of the models are listed in Table 6, and while a generic software like MATLAB can be found, SD is missing. Table 6 describes these models in terms of tools used, modelling method and model purpose.

Reference	Tool	Method	Model Purpose
[211]	Homer	Optimisation	Techno-economic impact/potential and optimisation of cost using scenario analysis.
[212]	-	Simulation	Optimising local self-consumption and self-sufficiency rate by adjusting prosumer to consumer ratio.
[213]	Homer	Optimisation	Optimising component sizes of community microgrid given technical and economic constraints.
[214]	Bi-level	Optimisation	Optimising social welfare by optimal distribution of economic revenue.
[215]	Homer	Optimisation	Optimising two scenarios (configurations) of microgrid to maximise economic benefit; each scenario with a different type of battery (storage) technology.
[216]	-	Workshop	Scenario analysis. Comparison of scenarios (options) of microgrid (supply technology) constitution with different levels of demand to aid decision making.
	Best Fit DES	Optimisation	Optimal matching of microgrid supply to demand; maximising economic, social and environmental benefits.
[217]	Homer	-	Virtual operation of a proposed DC microgrid.
	MATLAB Simulink	Simulation	DC supply.
[218]	-	Simulation	Virtual operation of a multi-energy microgrid.
	-	FMEA; Monte Carlo Simulation	Evaluation of the reliability of a microgrid.
[219]	MATLAB	Optimisation	Optimisation of reliability, economic benefit and environmental benefit of the microgrid.
[220]	MATLAB Simscape	Simulation	Comparison of performance of three DC microgrid configurations in terms of power

	Electrical library		reliability, power quality, economic impact and environmental impact.
[221]	-	Simulation; Optimisation	Evaluation of the safety of a hydrogen based microgrid using Failure Mode and Effect Analysis (FMEA).
[222]	MATLAB	Optimisation	Implementation and comparison of three metaheuristic optimisation algorithms of microgrid configuration that maximises reliability and minimises cost.
	MATLAB	Conditional programming	Implementation of a rule-based energy management system.
	MATLAB	Metaheuristic algorithm	Metaheuristic algorithm of the microgrid.
[223]	MATLAB	Optimisation	Optimisation of the size of renewable energy generation resources in a microgrid such that cost of energy is minimised, revenue to community is maximised and residential indoor temperature is most comfortable.
[224]	TRNSYS; EES	Simulation	Comparison of a proposed hybrid microgrid to an existing microgrid (modelled by real data) in terms of cost of energy.
[225]	Homer	Optimisation	Comparison of the economic cost of various microgrids.
[226]	-	Accounting	Comparison of different business models for operating a microgrid in order to evaluate the microgrid's economic feasibility.
[227]	MATLAB Simulink	Simulation	Evaluation of the performance of a proposed microgrid and compare it to alternative sources of energy.

Table 6 – Some bottom-up energy supply models from the literature

Furthermore, it has been observed that bottom-up models of energy systems are characterised by the first two laws of thermodynamics [54]. In other words, energy conservation and energy conversion losses respectively. Among the few models that model energy conservation or conversion losses, they are obscured in mathematical equations that are not intuitive and require a considerable proficiency in mathematical equations to understand. More generally, mathematical equations obscure the relationships between variables in a system, to the untrained. Therefore, there is a gap for bottom-up models that show energy conservation and conversion loss in a more intuitive graphical language, as well as the relationships between variables more generally. Another gap in the literature is that the conversion efficiencies are constants, even though conversion efficiency functions are widely known to be non-linear as documented in manufacturer's sheets of devices. Therefore, this study could also explore modelling non-linear conversion efficiency.

4.3 Methodology

4.3.1 System Dynamics in Bottom-up CEP

SD can be understood as presenting a model with two layers of sophistication: the diagram layer and the equation layer. In the case of CEP, different participants or stakeholders may be interested in the different layers, which opens up the potential for inter-disciplinary and trans-disciplinary collaboration because it can facilitate communication. Additionally, integration of separate models can be facilitated if they are modelled in SD especially when they share a common variable.

In addition to the general benefits of SD there are some specific benefits of using SD for bottom-up EP, which have been summarised in Table 7. Table 7 also shows the suitability of SD concepts to features of bottom-up energy supply models, while addressing the gaps identified in Section 4.2. For example, SD could offer realism via the principle of causal connectedness; which aims to ensure that relationships among variables in the model must be justified by evidence from the real system. Moreover, unlike other bottom-up models that obscure energy conservation and causal connectedness in equations, SD also expresses these graphically in SFD using causal links. Also note that a Stock can model energy or a power junction. A power junction distributes power in different directions from its origin without accumulating power; accumulated power is energy. Therefore, power junctions are expected to follow Kirchhoff's junction rule at all times, which can be expressed as: the sum of all power entering a junction must equal the sum of all power leaving the junction.

System Dynamics Concept	**Model Features and Benefits**
Flow	Power
Stock	Energy; Power junction
Constant	Parameters of devices; Initial states of devices

Material link	Energy conservation (graphically, in addition to equations)
Information link	Causal connectedness (graphically, in addition to equations)
Auxiliary (non-linear) variables	Non-linear energy conversion efficiency
Discrete feedback and auxiliary variables	Rule-based management of energy supply system
Stock and flow diagram	Modularity
	Ease of communication via generic diagrams which can facilitate collaboration and inter-disciplinary/trans-disciplinary research
Validity tests	Systematic validation of the modelling process and output

Table 7 – Mapping System Dynamics concepts to corresponding features and benefit to bottom-up supply-sided energy simulation model.

4.3.2 Modelling Process Overview

The modelling process in Figure 12 is based on the generalised modelling process in Chapter 3 (Figure 10). Figure 10 showed the three modelling stages (Problem Articulation, Model Conception and Model Formulation), as well as the inputs, outputs and associated validity tests. Figure 12 extends Figure 10 by repeating the last two modelling stages after the third stage. By the end of the third stage, the model would have been validated to data from Project SENSIBLE. The two extended stages modify the already valid model to include non-linear conversion efficiency. Hence, Figure 12 has five modelling stages that creates two valid models: one model after the third stage; and another model after the fifth stage. Therefore, the discussion section discusses the two output models and compares the effect of the modification (the two extra stages).

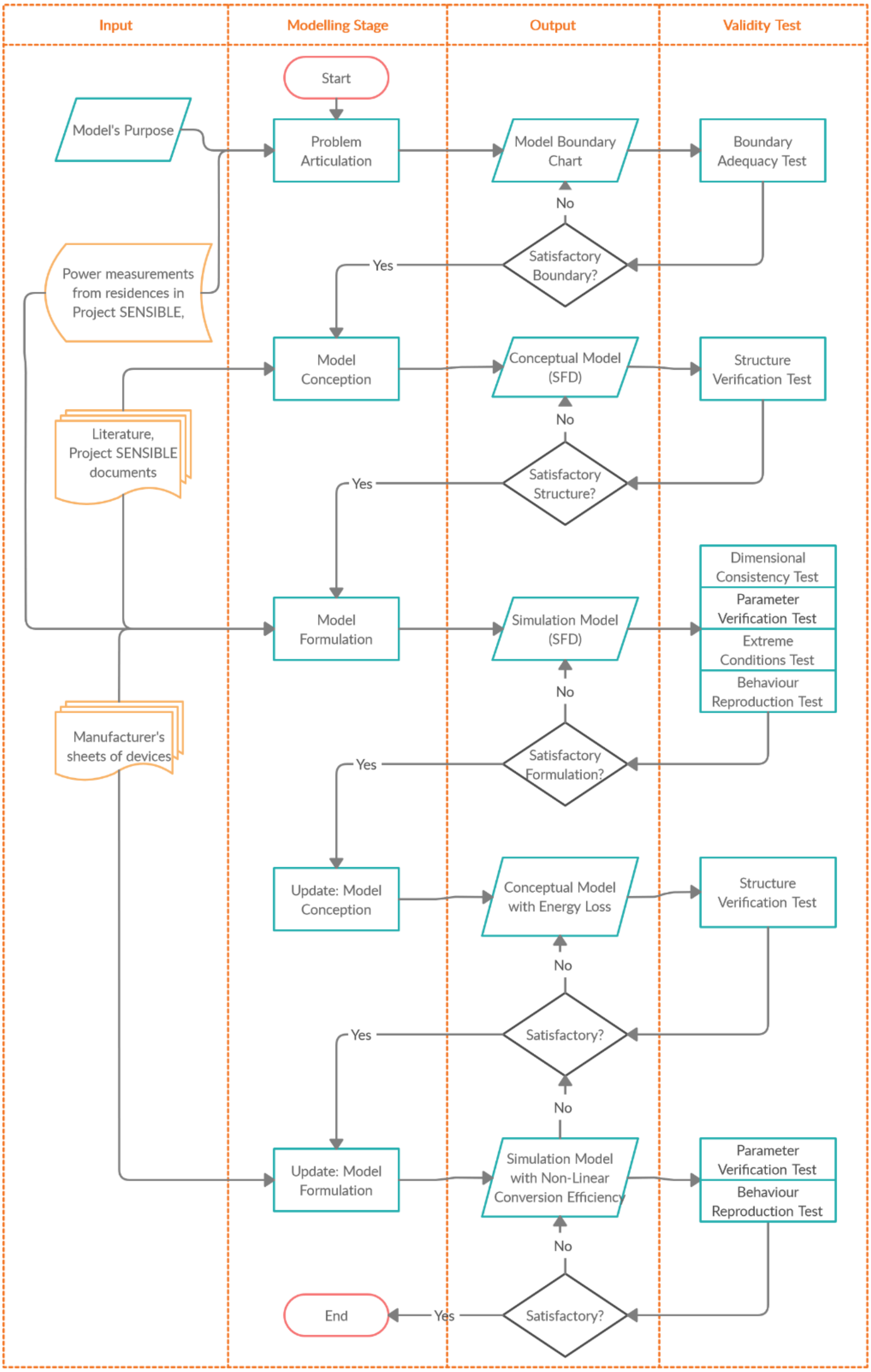

Figure 12 – Flowchart of the modelling process for Chapter 4 case-study

4.3.3 Project SENSIBLE

Validation of the model has been carried out using data from Project SENSIBLE (Storage Enabled Sustainable Energy for Buildings and Communities). The aim of SENSIBLE "is to understand the economic benefits that energy storage can bring to households, communities, and commercial buildings" [206]. SENSIBLE explores the use of energy storage at residential and community levels implemented in real communities. One of the communities is in The Meadows, Nottingham, UK. The plan was to implement a Community Energy System (CES) and several Residential Energy Systems (RES) made up of power electronic and communication devices.

The project has been well documented [228], [229], [238]–[246], [230]–[237]. Figure 13 shows the physical and communication architecture of SENSIBLE, showing some of the major elements in the system, while Table 8 provides brief, functional descriptions of the elements.

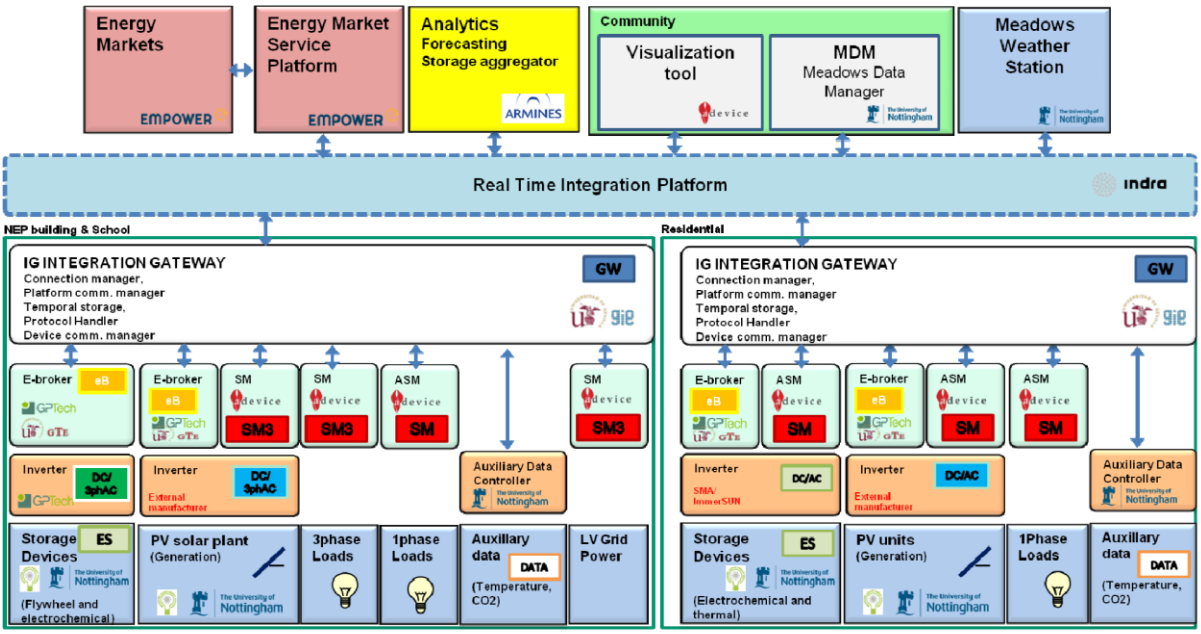

Figure 13 – Architecture schematic of project SENSIBLE in Nottingham (source: [237]*)*

Element	Function
PV Solar Plant	Generates Direct Current (DC) electricity from the sun.
Storage Device (electrochemical)	Chemical (Lithium) battery storage for electricity.
LV (Low-Voltage) Grid Power	Electricity source and sink connected to meters of end customers; the meters are connected to a low-voltage network.

Inverter	Inverters convert power between AC and DC. Storage inverters connect power supply to the battery storage in both directions; for charging from the grid or PV, and discharging to load. PV Inverter connects PV Solar Plant to the mains.
SM (Smart Meter 1 Phase) and SM3 (Smart Meter 3 Phases)	SM measures a single phase, while SM3 measures 3 individual phase nodes on a single-phase power system. This enables the energy meter to measure generation, storage, usage and grid power variables with a single meter.
eBroker	Smart grid management and optimisation. It is a distributed control-based system which aims to control the electrical grid stability and dynamically improves the quality.
Integration gateway (IG)	Integrates data coming from local/residential devices (smart-meters, converters, etc.) into the global/community real-time integration platform.
Real Time Integration Platform (RTIP)	Improves productivity and effectiveness in the exchange and management of information generated by various monitoring and control applications, while reducing the chances of error in data manipulation.
Meadows Data Manager (MDM); Energy Management System (EMS)	Centrally coordinates and implements analytical algorithms or micro-grid management functions.
Meadows Auxiliary Data Collector	Obtains local set of data that affects energy use which aggregates to community energy data set.
Demand forecast	Provides forecasts for the electric and heating demand for individual consumers.
PV forecast	Provides forecasts for the electricity generated from PV.
Energy Market and Services	Software emulation of energy market and market services.

Table 8 – Major elements of SENSIBLE Energy Systems and their functions

4.3.4 Data Sources

All data used in this case-study are secondary data, and the sourcing methods include archival research, desk research and existing data. The data used include qualitative and quantitative data from project documents, quantitative timeseries of power measured from residences and quantitative descriptions from manufacturer's specification sheets of the power devices in the residence. The residential power measurements were collected by members of SENSIBLE prior to this research and made available to this research on request. Several informal meetings were held with core members of the project team at the FlexElec laboratory of the University of Nottingham, where devices and algorithms for SENSIBLE were tested prior to deployment in the residences.

Power measurements at the residences were taken from the mains (AC) using a dedicated embedded kit. The available data is from three residences which have different combinations of devices: Grid + PV; Grid + Battery; Grid + Battery + PV. The data spans 14 days but only data for a day (from 00:00 to 23:59) is used for validation because plotting across multiple days obscures the minute-to-minute fluctuation in the behaviour of the simulated variables, while capturing the intra-day variation in the demand profile. The resolution of the measured data is 1-minute, covering 1440 data points per day, and the 1-minute measurement was achieved on the embedded kit by averaging the readings per second for each minute.

There were three measured power variables, which were all measured from the mains: import from the Grid; battery charging; and PV generation. However, two of the three variables provide information about two additional variables when the measured variables are negative: negative import is export; and negative battery charging is discharging. Additionally, the residential load demand is calculated from the measured data. Knowing that all five variables were measured from the mains (AC) allows for the simulation model to ignore power conversion between AC and DC before validating with measured data. Hence, the model created at the end of the third modelling stage (Figure 12) does not include power conversion. Power conversion is modelled in the second model, which is in the fourth and fifth modelling stages.

4.4 Discussion

4.4.1 Problem Articulation

The purpose of the modelling exercise is to create a valid simulation model of supply-side residential energy systems with non-linear conversion efficiency using a System Dynamics approach. Since the power measurements from the residences are recorded at 1-minute resolution, the time resolution of the simulation model is set to the same. Table 9 presents the Model Boundary Chart showing the major variables – and their respective units in parenthesis – from the real system that will be modelled (endogenous and exogenous) and those that will not be modelled (excluded). Forecasting, storage optimisation and energy market services are modules within SENSIBLE that rely on undisclosed proprietary algorithms and data, and the outcome of these modules are signals to the energy systems which have been represented as exogenous variables: Signal to charge battery from grid; and Signal to supply load from grid. For validity tests, all the major endogenous and exogenous variables listed in the Model Boundary Chart are considered relevant to the purpose of the model.

Endogenous	**Exogenous**	**Excluded**
• PV Consumption (W) • Import (W) • Export (W) • PV Charging (W) • Grid Charging (W) • Discharging (W) • Energy Management System (dimensionless) • Battery State of Charge (Wmin)	• Load demand (W) • PV production (W) • Signal to charge battery from grid (binary; dimensionless) • Signal to supply load from grid without battery discharge (binary; dimensionless) • Maximum battery SoC from grid charge (%; dimensionless) • Power ratings of the inverters (W) • Non-linear conversion efficiency of inverters (%; dimensionless)	• Auto discharge (W) • Reactive power (W) • Battery degradation (W)

Table 9 – Model Boundary Chart

4.4.2 Model Conception

A Conceptual Model explicates the system structure, which is the relationships among the relevant system components. A conceptual model of a RES with grid, battery and PV is shown in Figure 14; the numbers ‘1 0’ suffixed to the variables should be ignored because they are unique identifiers for variables that are similar in the RES models created in the same Vensim file. All arrows to and from the Energy Management System (EMS) are information links because the EMS controls the operation of the system, but it is not a power device. On the other hand, all the components connected to the material links are either power sources (PV Production, Grid), power storage (Battery), power drains (Consumption, Grid), power junctions (PV AC, PV Generated), or power devices (PV Charging, PV for Load, AC from PV, Grid Charging, Discharging, Import for Demand, Export). Each power device variable represents a function of a battery inverter, PV inverter or the cut-out equipment that connects the residence to the Grid.

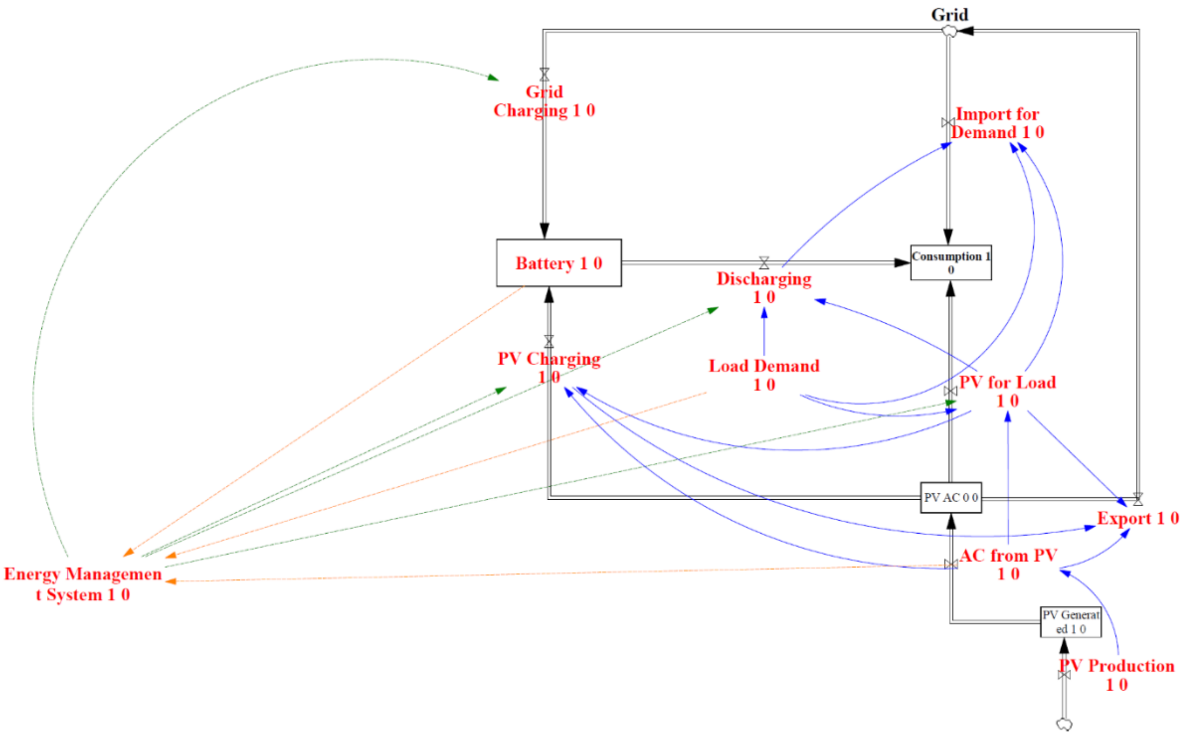

Figure 14 – Conceptual Model of a RES with grid, battery and PV showing causal dependencies among system elements using Stock and Flow Diagram.

Figure 15a shows a RES with battery and grid, while Figure 15b shows a RES with PV and grid. If Figure 14 is visualised as three bordering rectangles made from the double arrows, Figure 15a and Figure 15b can be seen as having only one of the rectangles, which highlights the modularity of the models. Furthermore, Figure 14 shows causal dependency among the components using arrows; a component is causally dependent on all the components that point to it. The material links (double arrows) illustrate energy conservation which tracks the flow of energy from generation at the PV panel or grid, to use for consumption of the residential load demand, to storage in battery, and to export to the Grid. The main hub of feedback is the Energy Management System (EMS); the orange dashed lines are incoming to evaluate the state of the system according to a rule-based logic (see Section 4.4.3.1), while the blue dashed arrows are outgoing to instruct components on the system's operation mode. The conceptual model can facilitate Systems Thinking because it is a diagram that explicates the interdependence in a system with feedback [70], [72], [247]. The simulation model is built on the conceptual model.

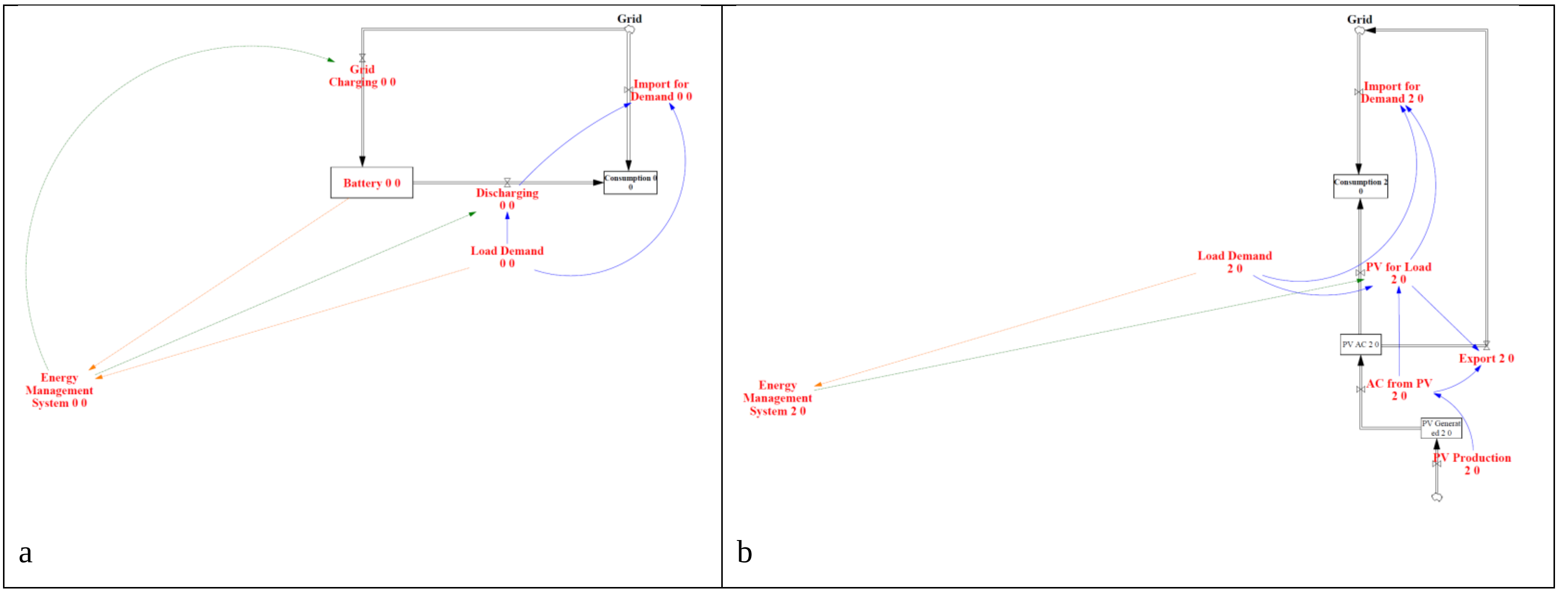

Figure 15 – Highlighting modularity of the SD models using conceptual models of two RES (a) with grid and battery, and the other (b) with grid and PV

The model conception stage is concerned with the Structure Verification validity tests. The conceptual models implement the following in fidelity with the real system: energy conservation such that energy can be accounted for from source to load, storage and export; enforcement of causal connectedness such that decision making elements make decisions using only information that is realistically available to them. Also, Import and Export are described as source and drain respectively, that balance the deficit and surplus in the mains without an explicit instruction from EMS to the grid interface to import or export; when charging from the Grid, the instruction is carried out from the battery inverter. Consequently, there are no green dashed arrows going to Import and Export from EMS in the diagrams of the conceptual models (Figure 14 and Figure 15).

4.4.3 Model Formulation

4.4.3.1 *System Operational Logic*

The operational logic of the simulation model can be presented on two levels: the first level illustrates the process on every time-step at a high level (Figure 16); then the second level expands on the rule-based logic of the Energy Management System (EMS; Figure 17). At every time-step, the state of the system, which is determined by the value of all variables in the system, serves as input to the EMS which then executes a rule-based logic (Figure 17), and arrives at an operation mode for the system. The operation mode is sent to the relevant power devices (or variables) who update their state according to their equations (see Section 4.4.3.2). This process is repeated for every time- step until the end of the simulation.

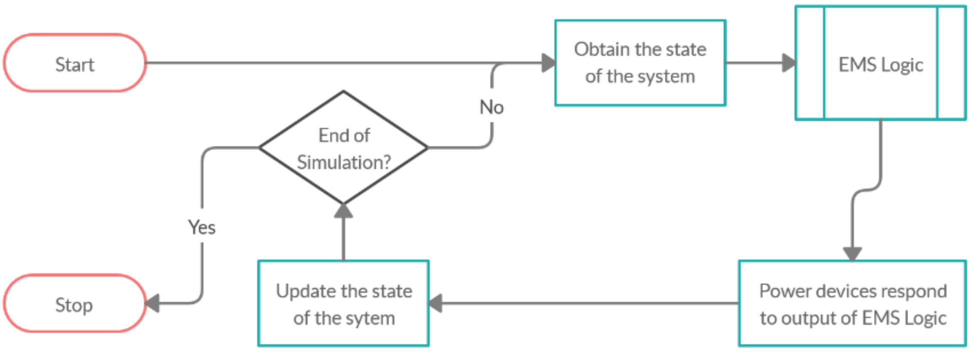

Figure 16 – High level process flow of each time-step of the simulation of the energy system

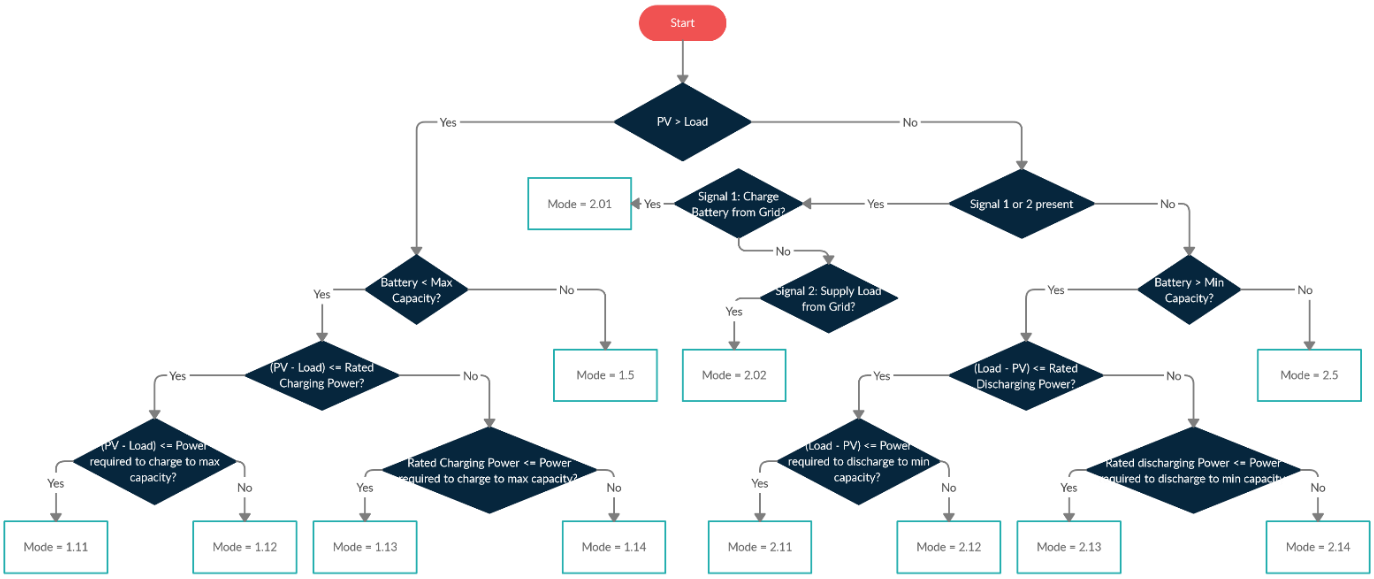

Figure 17 – Rule-based logic of the EMS

4.4.3.2 *Components Formulation*

Model variables can represent specific functions within a single real device. All exogenous variables can be found in the equations of endogenous variables. Consequently, the system components (endogenous variables) are expressed in Eq. 4.1 – Eq. 4.7 as equations for corresponding SD components which have been defined in **Error! Reference source not f ound.**, **Error! Reference source not found.** and **Error! Reference source not found.**. The symbols in the equations are described in Table 10.

$$SoC = \int_0^t (C_{PV} + C_I - D)\, dt \qquad \textit{Eq. 4.1}$$

$$E = PV - PV_{load} - C_{PV}, \qquad PV \geq Demand \qquad \text{Eq. 4.2}$$

$$I = \begin{cases} Demand - PV_{load} - D, & P_{supply\ capacity} \geq (Demand - PV_{load} - D), PV < Demand \\ P_{supply\ capacity}, & P_{supply\ capacity} < (Demand - PV_{load} - D), PV < Demand \end{cases} \qquad \text{Eq. 4.3}$$

$$C_I = \begin{cases} P_{charge\ to\ max}, & EMS = 2.01, P_{batt\ rated\ input\ AC} > P_{charge\ to\ max} \\ P_{batt\ rated\ input\ AC}, & EMS = 2.01, P_{batt\ rated\ input\ AC} \leq P_{charge\ to\ max} \end{cases} \qquad \text{Eq. 4.4}$$

$$C_{PV} = \begin{cases} PV - PV_{load}, & EMS = 1.11 \\ P_{charge\ to\ max}, & EMS = 1.12\ or\ 1.14 \\ P_{batt\ rated\ input\ AC}, & EMS = 1.13 \end{cases} \qquad \text{Eq. 4.5}$$

$$D = \begin{cases} Demand - PV_{load}, & EMS = 2.11 \\ P_{discharge\ to\ min}, & EMS = 2.12\ or\ 2.14 \\ P_{batt\ rated\ output\ AC}, & EMS = 2.13 \end{cases} \qquad \text{Eq. 4.6}$$

$$PV_{load} = \begin{cases} Demand, & EMS = 1.02\ or\ 1.11\ or\ 1.12\ or\ 1.13\ or\ 1.14\ or\ 1.5 \\ PV, & EMS = 2.01\ or\ 2.02\ or\ 2.11\ or\ 2.12\ or\ 2.13\ or\ 2.14\ or\ 2.5 \end{cases} \qquad \text{Eq. 4.7}$$

Symbol	**Description**
SoC	Battery State of Charge (SoC)
C_{PV}	Battery charging power from PV
C_I	Battery charging power from grid import
D	Battery discharging power
I	Power import from grid
E	Power export to grid
$Demand$	Load demand power
PV_{load}	Power from PV to service load demand
PV	Power produced by PV panel
EMS	Energy Management System
$P_{supply\ capacity}$	Maximum power allowed to be imported from the Grid
$P_{batt\ rated\ input\ AC}$	Rated input power to battery inverter
$P_{batt\ rated\ output\ DC}$	Rated output power from battery inverter

$P_{PV\ rated\ output\ AC}$	Rated output power from PV inverter
$P_{charge\ to\ max}$	Power required to charge battery to maximum

Table 10 – Description of symbols in equations of the system

4.4.3.3 *System Calibration*

The aim of system calibration is to adjust the model-parameters to match the behaviour of the real system, with reasonable explanation; system parameters are the exogenous variables of the system. For each system configuration (or residence), Table 11 shows the values assigned to the system parameters based on project documents (available from SENSIBLE's website), device specification sheets and measured data. The project documents were initially used to identify the model of power devices that were planned to be installed like batteries and inverters, then the specification sheets of the devices were referenced for the parameter values. However, it was discovered that in some instances, the measured data from the residences behave contrary to the expected behaviour from the planned devices. For example, the project documents specified an inverter with rated input AC power of 3300 W, but the measured data in one of the residences (Grid + Battery) showed that input AC power was capped at 2560 W. Therefore, that particular residence was calibrated with rated input AC power of 2560. Since no instance of power capping was observed in the other residence (Grid + Battery + PV), the residence was calibrated based on the specification of the project documents. In other words, planned device specifications were used unless contradicted by measured data in which case, the measured data was used. Core members of SENSIBLE also confirmed that not all the residences were deployed with the planned devices due to the varying sizes of the residences that were eventually involved in the project.

Residence	**Parameter**	**Value**	**Source**
Grid + Battery	Load Demand	Time series (W)	Measured data
	Rated Input AC Power (Battery Inverter)	2560 (W)	Measured data
	Battery Capacity	6.4 kWh	Device specification
	Battery Minimum Capacity	10% of Battery Capacity (kWh)	Device specification
	Battery Charge at Time 0	0.003 + Battery Minimum Capacity (kWh)	Measured data

	Signal: Charge Battery from Grid	Between 00:00 and 02:00	Measured data
	Signal: Supply Load from Grid Only	Between 02:00 and 04:00	Measured data
Grid + Battery + PV	PV Produced	Time-series (W)	Measured data
	Load Demand	Time-series (W)	Measured data
	Rated Input AC Power (Battery Inverter)	3300 (W)	Device specification
	Battery Capacity	6.4 kWh	Device specification
	Battery Minimum Capacity	10% of Battery Capacity (kWh)	Device specification
	Battery Charge at Time 0	902 + Battery Minimum Capacity (kWh)	Measured data
Grid + PV	PV Produced	Time-series (W)	Measured data
	Load Demand	Time-series (W)	Measured data

Table 11 – Some values and sources of parameters for the simulation models of the residences

Battery Charge at Time 0 (which is energy) is basically the result of calculated guesses to see which value matches the measured data. Since the measured data is power (not energy), Battery Charge at Time 0 could be known if other data are available like the battery charge at any time during the measured data, including when the battery was at its minimum capacity. However, no such data was available. Battery Charge was calculated from the measured data for every time-step, and the behaviour (shape of the plot) was similar to the modelled Battery Charge, but the initial value is not known which corresponds to Battery Charge at Time 0. Battery Charge at Time 0 is the intercept of the plot of the model's Battery Charge. Therefore, Battery Charge at Time 0 was calibrated by assuming that the minimum value of Battery Charge is equal to Battery Minimum Capacity, which is achieved by adjusting the intercept of the modelled Battery Charge (which is Battery Charge at Time 0) until the minimum of the plot equalled Battery Minimum Capacity.

Other time-series inputs to the model were also derived from measured data; PV Generation and Load Demand. PV Generation was measured directly, but Load Demand was calculated from the other measured data (PV Generation, Grid Import/Export, Battery Charge/Discharge). The two final parameters derived from the measured data are: the control signal to charge battery from the Grid only; and the signal to supply load from the Grid only. These are actually the outcome of proprietary algorithms that cannot be disclosed to researchers (as explained in Section 4.4.1) and, therefore, their outputs were made parameters instead. To identify the signals, the measured data was inspected for anomalous behaviour compared to what is expected, given the system operational logic (Figure 17). Then the signal is calibrated as active for the duration of the anomalous behaviour. Examples of anomalies is when the battery was charging from the Grid, when it should typically charge from PV only, which indicated the signal is active to charge battery from the Grid only. The other signal was identified as when the residential load was supplied by the Grid, even though the PV generation is not available, and Battery is charged; which indicated the signal is active to supply load from the Grid only. It was also helpful to know from the project documents that the algorithms would prefer to have the signals to be active at night-time when electricity is cheap.

4.4.3.4 *Simulation Model Diagram*

Figure 18 shows the simulation model of a residence with grid, battery and PV using SFD; which is elaborated from the conceptual model in Figure 14. Any component in the diagram is mathematically described in terms of all the components that point to it (see Section 4.4.3.2). The calibrated parameters are exogenous variables which are represented by variables that have no arrows pointing to them (see Section 4.4.3.3). For each residence, the calibrated model was run with two time-series inputs: Load Demand and PV Produced (see Section 4.3.4). The simulation was run for the duration of a day (1440 minutes) and the behaviour of the variables were validated against the measured data.

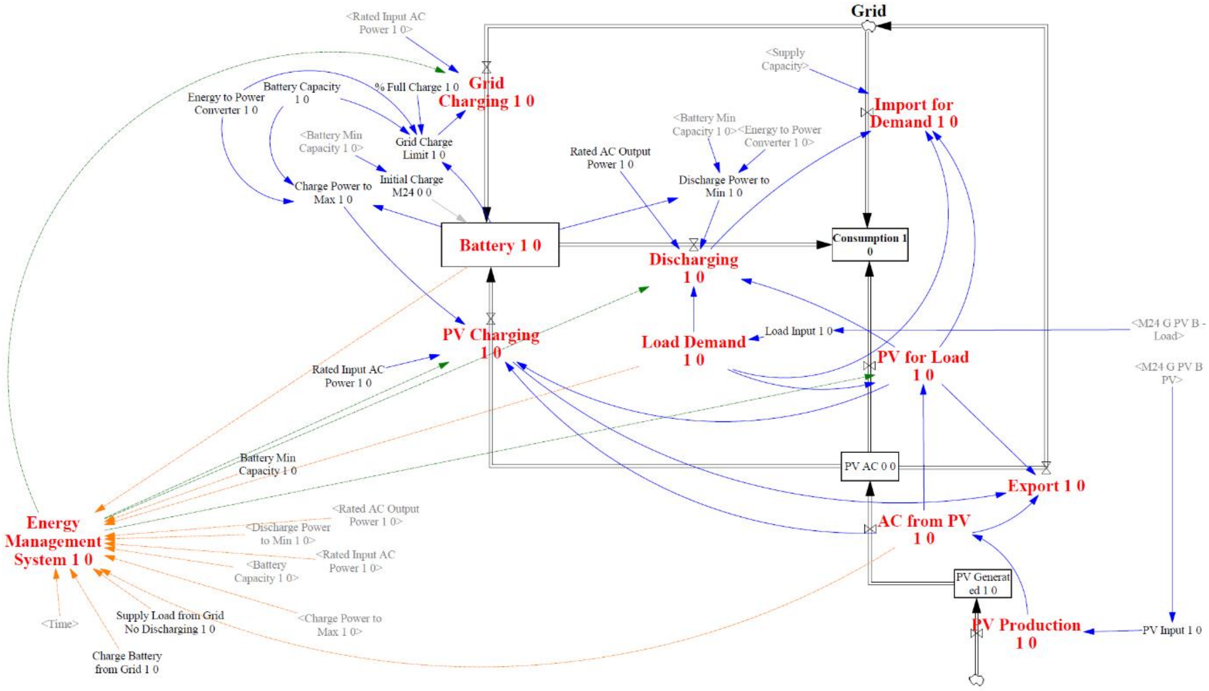

Figure 18 – Simulation Model of a Residential Energy System with grid, battery and PV using Stock and Flow Diagram.

4.4.3.5 *Validity Tests for Model Formulation*

The model's equations were checked using the integrated Units Checking tool in Vensim which highlighted no errors, and that confirms dimensional consistency of the variables' units. All parameter values were obtained from the project documents of SENSIBLE, device specification sheets, as well as measured data from the residences (see Table 11). Extreme values of variables were handled using logical expressions, for example, specifying rated power values of devices to limit the maximum power that may flow through an inverter. Only one conversion variable in the model had no real-world counterpart but it was used in order to balance the units; labelled "Energy to Power Converter", which has a value of 1 and a dimension of 1/time. It is used in the equations of three variables where a power value is to be determined from energy values: Charge Power to Max; Discharge Power to Min; and Grid Charge Limit. Conversion variables have been used in examples in [72].

Energy conservation was confirmed by comparing the total energy in the system at the end of the simulation on the one hand, with energy at the start plus energy into the system minus energy exported on the other hand. The result is that both values are the same which confirms energy conservation. An alternative way to confirm this is to check that the power junctions PV AC and PV Generated are zero throughout the simulation, based on Kirchhoff's junction rule.

Theoretically, there could be moments when Load Demand exceeds the combined rated values of all power sources such that the Load Demand cannot be adequately served. Unserved load was monitored, but not handled in the logic of the EMS because the detail of this was not found in the project documentation. Given that the input Load Demand to the model is data from real residences, it should not lead to unserved load, unless the specification of simulated devices were less than the real devices, which will prompt recalibration. Nonetheless, monitoring unserved load serves as an additional validity test, and there were no unserved Load Demand in the final simulation models.

4.4.4 Behaviour Reproduction

Behaviour is the change in the value of a variable over time, and it can be visualised by a time-series plot of the variable. The aim in behaviour reproduction validity test is to have the plots of a variable in the simulation correspond to the same measured variable in the real system with minimal error or a reasonable explanation. The behaviour of variables in the simulation models match the behaviour of the real residences, although not perfectly, for all the endogenous variables, some of which are shown in the plots in Figure 19. The Mean Absolute Error and Root Mean Squared Error for Figure 19a are 0.02W and 0.15W respectively, while for Figure 19b, they are 16W and 33W respectively. The minor error can be explained by downsampling that occurs in the embedded kit, during measurement of power values at the residences, some of which serve as input to the simulation. The error is discussed in the next section (Section 4.4.5). Having addressed the concerns of other validity tests in previous sections, which have culminated in the model outputs matching the behaviour of measured values, the created model can be considered valid.

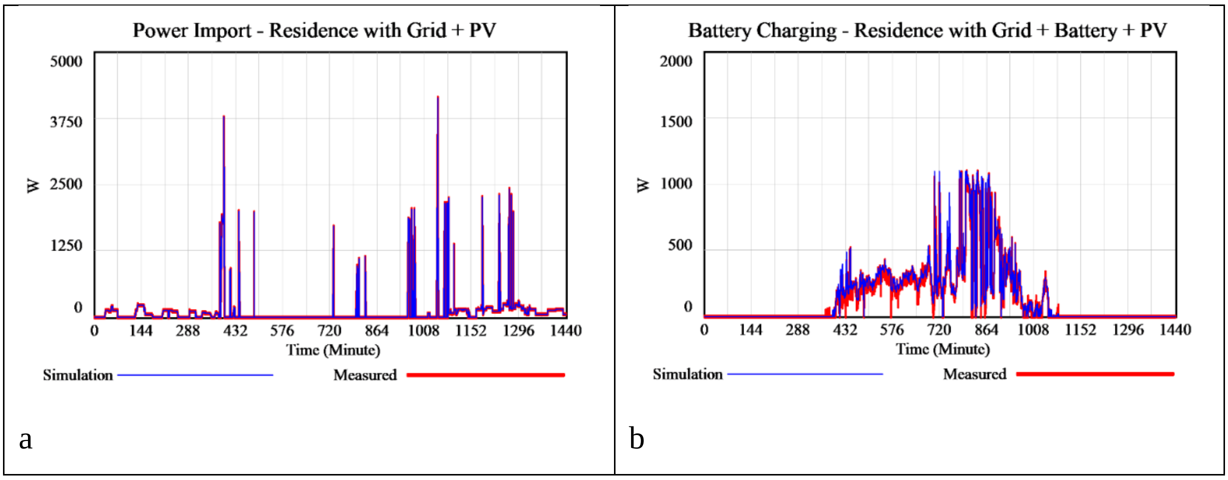

Figure 19 – Comparing behaviour of the measured data to the simulation model without conversion efficiency, for two simulated residences

4.4.5 Error Analysis of Behaviour Comparison

Figure 20 and Figure 21 show the differences between the simulation and measured data in Import, Export, Charging and Discharging. The errors are calculated as measured value minus simulation value; import and export errors take only positive error values, while charging and discharging errors take both positive and negative values. There is a relationship among the four variables: whenever discharging error is positive, export error takes the same value; whenever discharging error is negative, import error takes the same magnitude but positive value; whenever charging error is positive, import error takes the same value; whenever charging error is negative, export error takes the same magnitude but positive value. Since Import and Export are calculated from Charging and Discharging (which are simulated from the exogenous inputs of Load Demand and PV Production), the source of the errors noticed in Import and Export are actually errors that originated in the simulation of Charging and Discharging, but eventually impact Import and Export because of the implementation of Import and Export as balancing source and drain respectively.

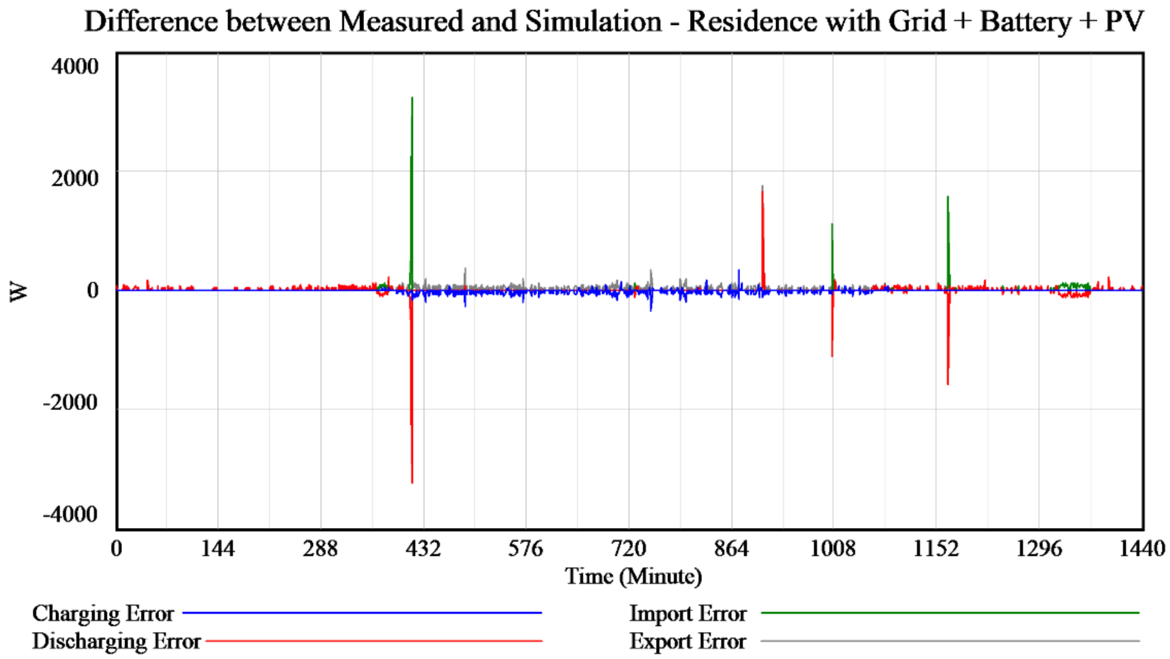

Figure 20 – Differences between measured and simulation values for charging, discharging, import and export.

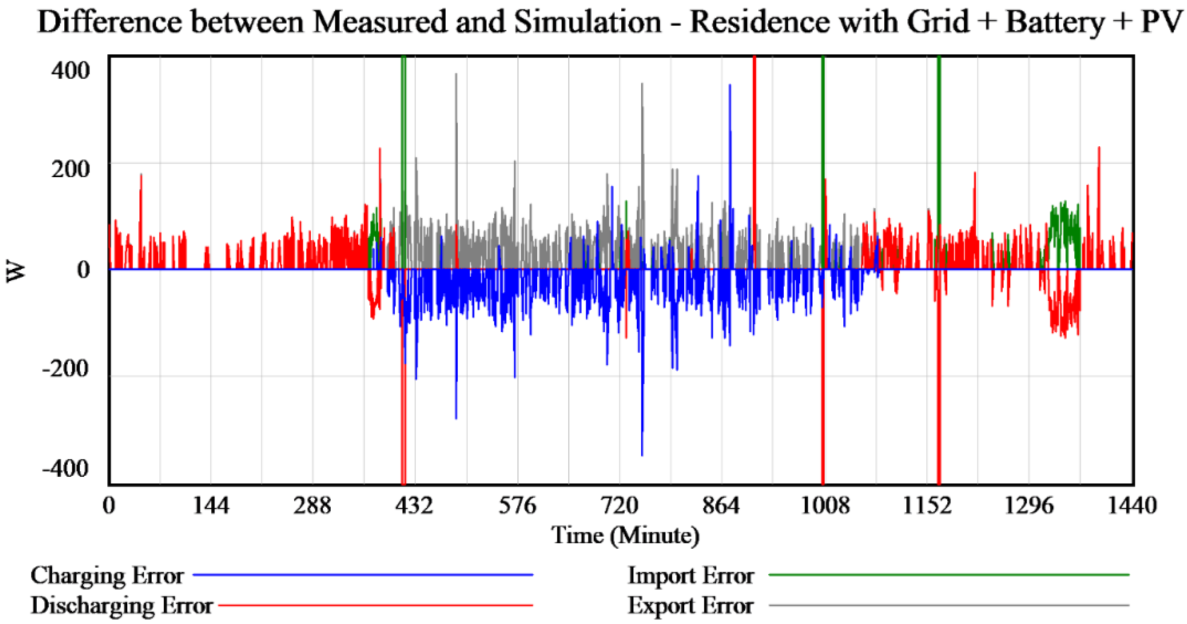

Figure 21 – Zoomed in: Differences between measured and simulation values for charging, discharging, import and export.

The discrepancy between the simulation and measured data can be explained by downsampling that occurs during measurement. Downsampling is the process of reducing the resolution or frequency of a time-series data from a higher resolution (e.g. seconds) to a lower resolution (e.g. minutes). As mentioned earlier, the residential power measurements were recorded on the mains at 1-minute intervals. Since the measurements taken from the residences are actually averaged power over 60 seconds at the time of measurement, the measurements were downsampled from 1 second to 60 seconds, because power (W) is measured in seconds. From the perspective of the higher resolution (1 second), the downsampled variable is assumed to be at that average value for the duration of the 60 seconds. Therefore, downsampling flattens the values of the lower resolution over the duration of the higher resolution.

Among the measured data, only Load Demand and PV Produced are input to the simulation, and the simulation calculates the other variables. All the simulated power values are calculated from the two downsampled measured input (at the downsampled resolution), but then compared with corresponding measured power values which are also downsampled at measurement. Comparing two values (e.g. measured Import vs simulated Import) on the same resolution where one value is first downsampled could lead to significant difference.

The argument that the difference is due to downsampling can be made using the simulation equations for the sources of the error expressed in terms of the two downsampled input variables: Charge and Discharge expressed in terms of Load Demand and PV Production as in

Eq. 4.8 and *Eq. 4.9*, which are specific cases of Eq. 4.5, Eq. 4.6 and Eq. 4.7. Generically, the two downsampled variables can be expressed as p (*Eq. 4.10*) and q (*Eq. 4.11*). The error, e_q , (*Eq. 4.14*) will be defined as the difference between the two variables where v is first downsampled at measurement (*Eq. 4.12*), while v' is calculated from the downsampled inputs (*Eq. 4.13*).

$$C_{PV} = PV - Demand, \qquad EMS = 1.11, \qquad PV > Demand \qquad \textit{Eq. 4.8}$$

$$D = Demand - PV, \qquad EMS = 2.11, \qquad Demand > PV \qquad \textit{Eq. 4.9}$$

$$p = \frac{1}{n}\sum_{t=1}^{n} x_t \qquad \textit{Eq. 4.10}$$

$$q = \frac{1}{n}\sum_{t=1}^{n} y_t \qquad \textit{Eq. 4.11}$$

$$v = \frac{1}{n}\sum_{t=1}^{n} x_t - y_t, \qquad x_t > y_t \qquad \textit{Eq. 4.12}$$

$$v' = p - q, \qquad p > q \qquad \textit{Eq. 4.13}$$

$$e_q = v - v' \qquad \textit{Eq. 4.14}$$

Where x_t is the first term at t seconds, y_t is the second term at t seconds, n is the factor of downsampling in measurement (n=60 when going from 1 second to 1 minute), p is downsampled x in n seconds which is measured, q is downsampled y in n seconds which is measured, v is the measured but downsampled variable (in n seconds), v' is the simulated but downsampled variable (in n seconds), e_q is the difference between the measured variable v and the simulated variable v'. Assume t and n are natural numbers. Therefore, e_q is what could appear as the measured import or export even when the simulated import or export is zero.

To estimate the range of values of error e_q, consider two situations in Table 12 where y is the same for all n seconds while x is $0.5y$ for $n/2$ seconds and $1.5y$ for $n/2$ seconds; and where y is the same for all n seconds while x is 0 for $n-1$ seconds and ny for 1 second. Situation 2 is more extreme than Situation 1 in terms of difference within the first term, but these are theoretical situations. Therefore, in Situation 1, it is possible to observe a reading in the measurement of variables like Import and Export while they are zero in the simulation, up to a magnitude that is half of the second term (q') in v'. In Situation 2, the observed reading could be as high as the multiplication of the downsampling factor (n) to the second term; as high as 60 times (or 5900% more than) the second term when downsampling from seconds to 1 minute.

Practically, the magnitude of errors from Charging and Discharging are bounded by rated input and output power of the battery inverter. Looking at Figure 20, the highest error magnitude is 3256 W and 356 W for Charging and Discharging respectively which are both less than the rated input and output power of the inverter at 3300 W.

Source Equation	**Situation 1:** y is the same for all n seconds while x is $0.5y$ for $n/2$ seconds and $1.5y$ for $n/2$ seconds	**Situation 2:** y is the same for all n seconds while x is 0 for n-1 seconds and ny for 1 second
Eq. 4.10	$p = y$	$p = y$
Eq. 4.11	$q = y$	$q = y$
Eq. 4.12	$v = \frac{2}{n}\sum_{t=1}^{n/2} 0.5y$	$v = \frac{1}{1}\sum_{t=1}^{1} ny$
	$v = \frac{2}{n} \times \frac{n}{2} \times 0.5y = 0.5y$	$v = ny$
Eq. 4.13	$v' = y - y = 0$	$v' = y - y = 0$
Eq. 4.14	$e_q = v - v' = 0.5y - 0 = 0.5y$	$e_q = v - v' = ny - 0 = ny$

Table 12 – Estimating the range of error e_q

4.4.6 Model Modification

4.4.6.1 *Non-linear Conversion Efficiency Curve*

After simulating and validating the model of the system based on the measured data from SENSIBLE, the model was modified to include non-linear energy conversion efficiency. All the inverters in the system (battery inverter and PV inverter) convert power between AC and DC, and this is carried out based on non-linear efficiency curves. The non-linear efficiency curves are typically provided in the specification sheet of the inverter in terms of the ratio between the output power and the rated output power; see Figure 22 for the curve provided by the inverter manufacturer (SMA) showing the ratio on the x-axis and the efficiency on the y-axis; PV2AC refers to PV Inverter converting PV power from DC to AC for the mains; AC2BAT refers to Battery Inverter converting the mains power from AC to DC for battery charging; BAT2AC refers to Battery Inverter converting battery power from DC to AC for the mains. It can be seen in Figure 22 that outputting low power relative to the rated power of the inverter could lead to high losses of power because the efficiency would be very low. Therefore, inverter size, which is specified in terms of rated power, is important to minimise losses, considering the typical power consumption of a residence.

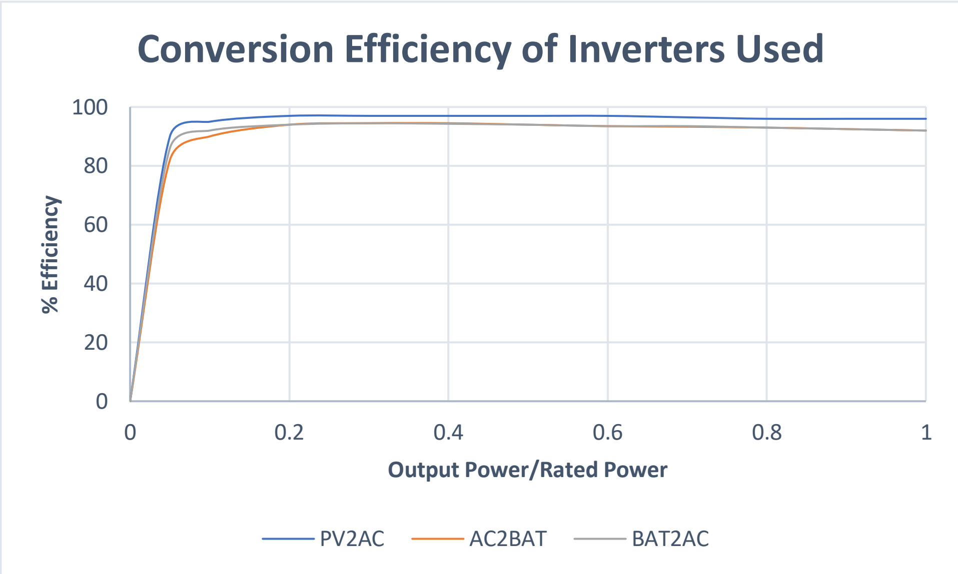

Figure 22 – Conversion efficiency of inverters modelled in the residential energy simulation.

4.4.6.2 *Model Conception*

The structure of the model Figure 14 has been modified to include non-linear conversion efficiency which leads to non-linear loss, as shown in Figure 23. Causal dependency is shown as in the previous models, but the material links (double arrows) also show energy losses from the conversions as part of energy conservation.

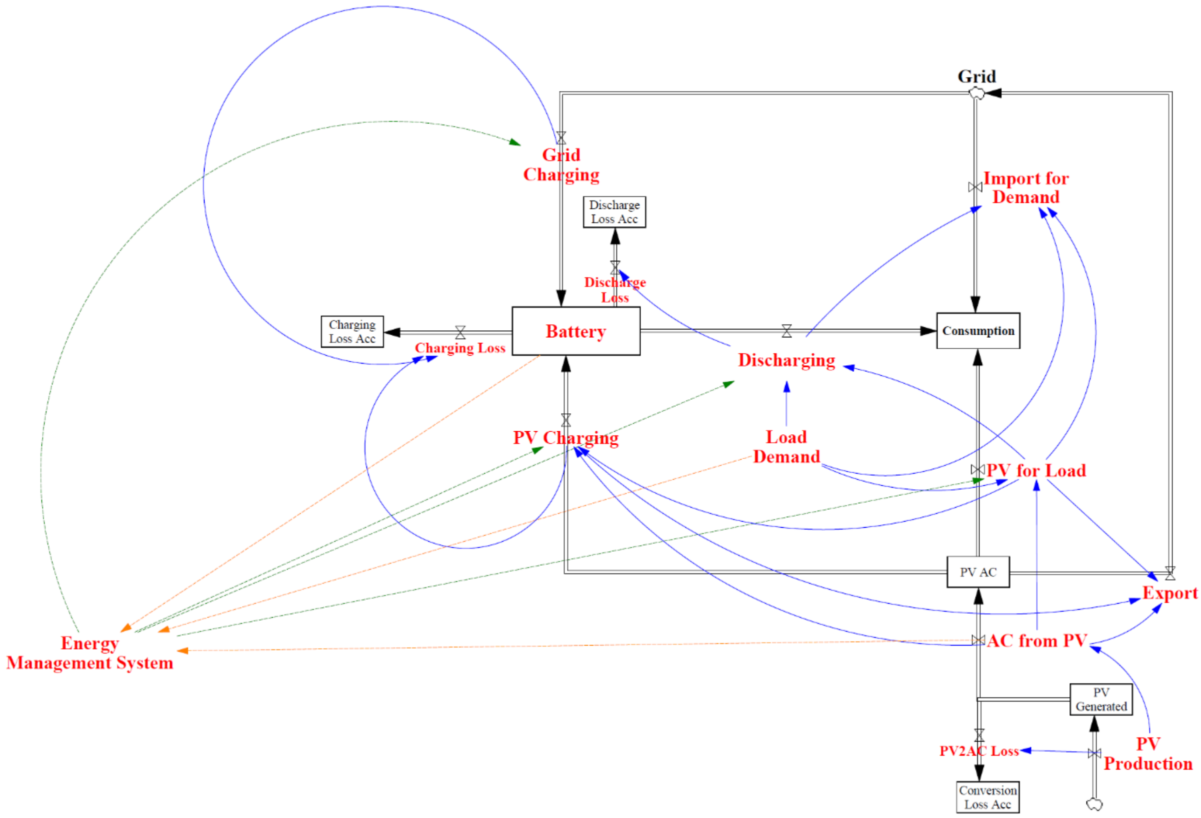

Figure 23 – Conceptual Model of a Residential Energy System with grid, battery, PV and losses from energy conversion, and showing causal dependencies among system elements using Stock and Flow Diagram.

4.4.6.3 *Model Formulation and Calibration*

The formulation of the components has been updated to include the non-linear conversion efficiency; see Eq. 4.15 to Eq. 4.20 for the components that changed and Table 13 for description of the new symbols. The new parameters of non-linear efficiency curves have been calibrated according to the manufacturer's specification sheet of the inverters; see Figure 22. Simulation models were run for the same duration of 1440 minutes, like the simulation model without energy conversion.

$$SoC = \int_0^t \left(C_{PV} + C_I - L_{charging} - L_{discharging} - D\right) dt \qquad \textit{Eq. 4.15}$$

$$C_{PV} = \begin{cases} PV_{AC} - PV_{load}, & EMS = 1.11 \\ P_{charge\ to\ max} / f_{batt\ AC2DC\ output}\left(\dfrac{P_{charge\ to\ max}}{P_{batt\ rated\ output\ DC}}\right), & EMS = 1.12\ or\ 1.1 \\ P_{batt\ rated\ input\ AC}, & EMS = 1.13 \end{cases} \qquad \textit{Eq. 4.16}$$

$$L_{charging} = (C_{PV} + C_I) \times \left(1 - f_{batt\ AC2DC\ input}\left(\frac{(C_{PV} + C_I)}{P_{batt\ rated\ output\ DC}}\right)\right)$$ *Eq. 4.17*

$$L_{discharging} = D/\left(f_{batt\ DC2AC\ output}\left(\frac{D}{P_{batt\ rated\ output\ DC}}\right)\right) - D$$ *Eq. 4.18*

$$PV_{AC} = PV_{DC} \times f_{PV\ DC2AC\ input}\left(\frac{PV_{DC}}{P_{PV\ rated\ output\ AC}}\right)$$ *Eq. 4.19*

$$L_{PV} = PV_{DC} \times \left(1 - f_{PV\ DC2AC\ input}\left(\frac{PV_{DC}}{P_{PV\ rated\ output\ AC}}\right)\right)$$ *Eq. 4.20*

Symbol	**Description**
$L_{charging}$	Power loss from conversion (AC to DC) for battery charging
$L_{discharging}$	Power loss from conversion (DC to AC) for battery discharging
L_{PV}	Power loss from conversion (DC to AC) of PV power produced
$f_{batt\ AC2DC\ output}\left(\frac{x}{y}\right)$	Non-linear conversion efficiency function of battery inverter, from AC to DC, in terms of output (x) from the inverter and the rated output of the inverter (y).
$f_{batt\ AC2DC\ input}\left(\frac{x}{y}\right)$	Non-linear conversion efficiency function of battery inverter, from AC to DC, in terms of input (x) to the inverter and the rated output of the inverter (y).
$f_{batt\ DC2AC\ output}\left(\frac{x}{y}\right)$	Non-linear conversion efficiency function of battery inverter, from DC to AC, in terms of output (x) from the inverter and the rated output of the inverter (y).
$f_{PV\ DC2AC\ input}\left(\frac{x}{y}\right)$	Non-linear conversion efficiency function of PV inverter, from DC to AC, in terms of input (x) to the inverter and the rated output of the inverter (y).

Table 13 – Description of new symbols in equations of the system with non-linear efficiency curve

4.4.6.4 *Simulation Model Diagram*

Figure 24 shows the simulation model of a residence with grid, battery, PV and non-linear conversion efficiency using SFD. Compared to Figure 18, the updated variables are the non-linear conversion efficiency, and the variables they affect. The simulation was run for the duration of a day (1440 minutes) and the behaviour of the variables were validated in comparison to the model without energy conversion.

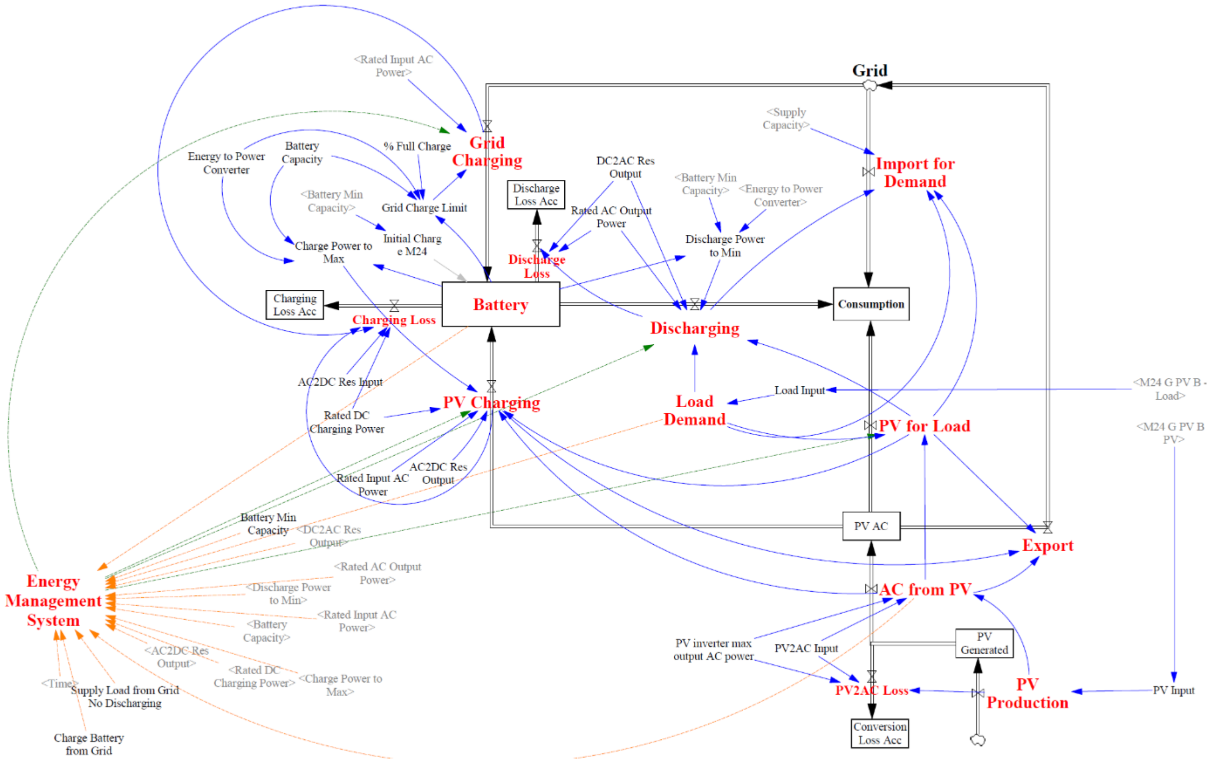

Figure 24 – Simulation Model of a Residential Energy System with grid, battery, PV and losses from energy conversion, and showing causal dependencies among system elements using Stock and Flow Diagram.

4.4.7 Effects of Non-Linear Conversion Efficiency

The aim of this section is to compare the behaviour of the simulation with non-linear conversion efficiency to the simulation without conversion efficiency using results from the simulation. First the effect of conversion efficiency will be discussed in general, then the effects of non-linear efficiency in particular. Figure 25 shows simulation without energy conversion (WOEC) and simulation with energy conversion (WEC). The simulation WOEC has been discussed in sections 4.4.2 to 4.4.4, and the conversion efficiency implemented in the simulation WEC has been discussed in Section 4.4.6. The model WOEC effectively has a constant conversion efficiency of 100%, while the model WEC has a non-linear conversion efficiency as discussed in Section 4.4.6. Therefore, the comparison between WOEC and WEC can be understood as a comparison between a constant and a fluctuating conversion efficiencies. The importance of exploring the effects of conversion efficiency is that it has implication on decision-making about the size of inverter, with the aim to choose the size that results in the highest conversion efficiency, given the usage. Methodologically, it is important in decision-making.

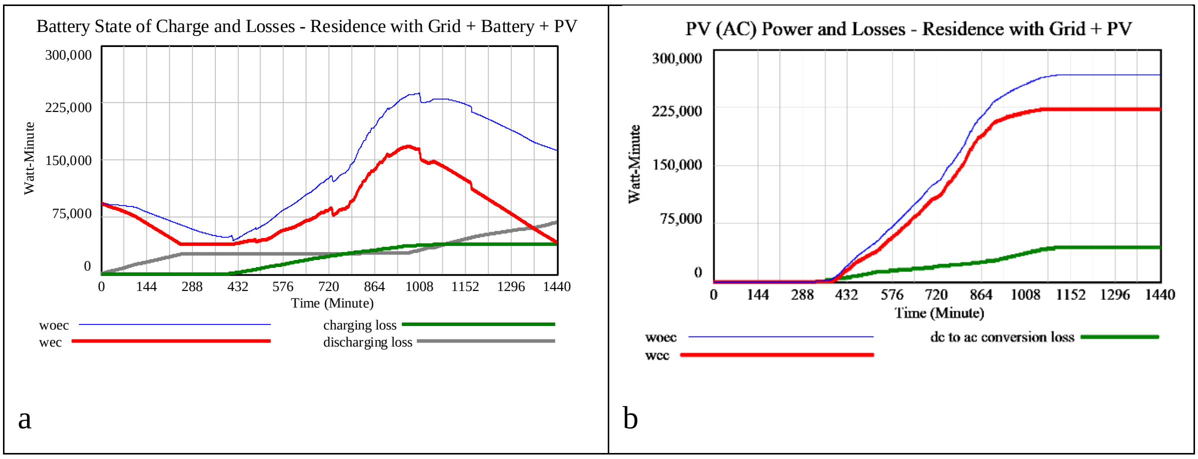

Figure 25 – Showing the influence of losses from conversion on battery SoC and energy from PV in two residences.

Figure 25a shows the effects of the conversion efficiency on battery SoC, in terms of energy (Wmin). In the simulation WEC, Battery SoC at any time is the cumulative summation of Charging, Discharging, Charging Loss and Discharging Loss. When charging (when SoC is rising), the slope in WEC is less steep than in WOEC because some of the energy is lost in conversion, which corresponds to increase in charging loss. On the other hand when discharging (when SoC is declining), the slope in WEC is steeper than in WOEC because more energy is required to service the same load while accounting for conversion losses, and this corresponds with rise in discharging loss. Similarly, Figure 25b shows the effects of the conversion efficiency on usable energy (Wmin) produced from PV. PV Produced is modelled as power (W) but plotted as energy (Wmin), which is accumulated power, for clarity of illustration. The usable PV power (AC) from simulation WEC is always less steep than the simulation WOEC, because there is always conversion loss in simulation WEC which is increasing. For both Battery SoC (Figure 25a) and PV Power across the residences (Figure 25b), the difference between WOEC and WEC can be explained by the losses in WEC. However, Figure 25 does not show the effects of non-linearity of the conversion efficiency.

The non-linear efficiency curves were shown in Figure 22. Figure 26 shows the non-linear effects of the conversion efficiencies for the same residences in Figure 25, in terms of power (W), focusing on: Battery Charging and Charging Loss in Figure 26a; then PV and PV Loss in Figure 26b. Since higher power (as it approaches the rated power) results in higher efficiency, and efficiency is inversely proportional to loss, then higher proportion of loss can be observed at lower power values, which explains why the power loss seems to spike whenever the charging power (Figure 26a) or PV power (Figure 26b) dips, and vice versa. At some low power levels towards the beginning and end of Figure 26b, the losses are almost the same as the utilised power. In addition to the consideration of inverter size, this has significant implication for deciding whether to convert power at low power levels or find a way to store the power directly without conversion; and perhaps source the required low power from more efficient sources.

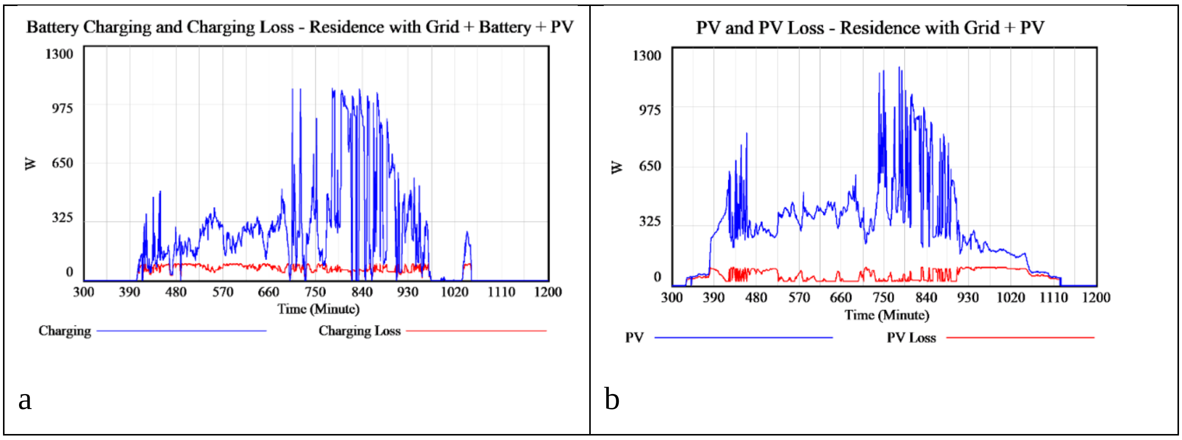

Figure 26 – Effects of non-linearity of the conversion efficiency

Prior to the addition of non-linear energy conversion efficiency, the model was found to be valid. After the addition of non-linear energy conversion efficiency, the model behaved as expected, as discussed in this section. Therefore, the second model can also be considered valid. The second model will be used in subsequent chapters.

4.5 Conclusion

This chapter addressed part of the fourth thesis aim which is to demonstrate the application of SD in the gaps identified in Chapter 2, by focusing on the validity of supply-side simulation from the bottom-up. Therefore, this chapter addressed the third thesis objective, which is to develop a valid simulation model of a supply-side energy system from the bottom-up using SD.

Furthermore, crucial features of bottom-up energy models, like energy conservation, energy loss and causal relationship among system elements, have been presented in simple diagrams as SFD. Meanwhile, the rigour traditionally provided by equations to these features was maintained. Additionally, modularity of the models was shown in the diagrams. The use of diagrams could aid collaboration and communication about the models across different expertise and stakeholders in EP. Also, the importance of modelling non-linear conversion efficiency was explored as it affects choice of inverter size, as well as model accuracy given the choice to model it or not.

In their current state, the models could be readily integrated with other SD models that have common variables, and this is explored in Chapter 8. Furthermore, the model could be used to carry out techno-economic and techno-environmental impact analyses, which is explored in the next chapter.

5 Decision-making Analysis using Supply-side SD Models

5.1 Introduction

Valid bottom-up supply-side SD models of RES have been created in Chapter 4. However, the models have not been used to carry out analyses for decision-making. The aim of this chapter is to demonstrate the use of the SD model to analyse the sustainability of a RES for decision-making, which is the fourth thesis objective. The literature of similar analyses is surveyed and the case-study is designed to address gaps in the literature, while achieving the thesis objectives. The case-study is designed using the SA framework from Chapter 3, and analyses are carried out.

High resolution (1-minute) load profile and PV profile are generated from an existing synthetic model and used as input to the SD model. Five types of residences are modelled in the SD model and all are analysed in different scenarios. Battery degradation is also modelled. Approaches to estimating the Performance Indicators into the future are explored and resulting errors are analysed, while taking account of the behaviour of the sustainability indicators over time. Energy Loss Ratio is introduced as a technical Performance Indicator. Scenarios with different operation strategies as well as different consumer types are considered. The effects of modelling battery degradation and non-linear conversion efficiency are also explored.

5.2 Literature Review

5.2.1 The State of The Art

The scope of the literature reviewed has been limited to studies that carry out assessments of RES based on Performance Indicators in at least one of three sustainability dimensions which can aid decision making: technical; economic or environmental. A summary of the review is presented in Table 14. The reviewed studies model individual residences, however it is worth mentioning other studies that do not model individual residences but have significance on decisions taken at the level of individual residences, which include models of building clusters [248], [249] and microgrids [250], [251].

System Components	Methods	Tools	Control Levers	Performance Indicators	Ref
PV Battery Grid Electricity Market	Simulation Parametric analysis	MATLAB	Tariff Battery (with or without) FiT Other subsidies	SCR SSR PBP LCOE	[252]
PV Battery Grid	Simulation Optimisation	SimSES (simulation of stationary energy storage systems)	Tariff Energy management strategy Battery Degradation Load profile PV Generation profile	IRR SCR SSR	[253]
PV Grid	Financial model Sensitivity analysis	System Advisor Modelling Software	Tariff Load profile PV size PV tilt angle	Yield factor Capacity factor Performance ratio LCOE NPV IRR PBP	[254]
PV Battery	Financial model	System Advisor Model (SAM)	Weather data (wind speed, temperature) Battery (with and without)	Energy output Projected cost ROI PBP	[255]
PV Battery	Machine learning (K-means clustering)		Tariff Load profile PV generation profile	NPV	[256]

	Mathematical simulation Optimisation		Battery size		
PV Wind Grid	Mathematical simulation	RETScreen (for solar and wind information)		LCOE NPV IRR PBP Coverage of annual demand	[257]
PV	LCA	EnergyPlus	Building geometry Building spaces Building thermal zones	Carbon emissions Energy cost Operating cost	[258]
PV Battery Grid	Mathematical simulation		Load profile Configurations of PV and battery PV generation capacity Battery capacity Insolation	SCR SSR Consumption savings of the electric grid IRR Grid parity	[259]
PV Wind turbine Battery	Simulation Life Cycle Evaluation model (based on the net present value NPV) Sensitivity analysis	HOMER	System Operation constraints	*NPV* *LCOE* Energy storage life System shortage capacity Atmospheric pollution emissions	[260]

PV battery heat pump	Sensitivity analysis		Load profile Gas profile Gas tariffs Carbon tax Subsidies	GHG (avoided lifecycle) Payback period for GHG SSR Import peak to average ratio (IPAR) Export peak to average ratio (EPAR) Maximum import power peak Export power peak to the grid - Grid Impact NPV IRR PBP Cost reduction	[261]
Battery Grid	Mathematical simulation Monte Carlo simulation		Tariff Energy Management Strategy	NPC LCOE NPV IRR	[262]
PV Grid	Simulation LCA Sensitivity analysis	RETScreen (renewable energy technology assessment tool) SimaPro 7.1 (Life Cycle	PV cost Energy cost PV production cost PV rated power PV production power consumption	GWP100 (Global Warming Potential at 100 years) PER (Primary Energy Requirement) NPV IRR	[263]

		Assessment tool)		PBP BCR (Benefit Cost Ratio) Energy Production Cost	
Battery	Simulation Monte Carlo Simulation (a sensitivity analysis)	MS Excel (Visual Basic application) for simulation of operation MATLAB (generate synthetic load for a year from 2 months)	Tariffs (ToU for price arbitrage) Battery type	NPC NPV LCOE IRR Grid Capacity Utilisation CO_2 Avoided SO_2 Avoided NO_x Avoided	[264]
PV Battery Grid	Simulation Optimisation Sensitivity analysis (battery storage capacity on MILP)	DER-CAM (Distributed Energy Resources Customer Adoption Model)	Tariff Load profile FiT incentive Battery cost Battery capacity Solar irradiance	FiT revenue	[265]
PV Grid Battery	Simulation	PVsyst system performance simulation tool	Load profile Weather condition Shading Grid (with and without)	PBP PR (Performance Ratio)	[266]

		PVGIS (Photovoltaic Geographic Information System) pre-sizing			
PV Battery Grid	Mathematical simulation		Load profiles Battery (with and without) Battery capacity Subsidies (battery retail prices)	SSR SCR LCOE LCOS (Levelised Cost of Storage)	[267]

Table 14 – Review of literature on assessment of the performance of residential energy systems

Table 14 profiles the studies based on the following: system components; methods used; tools utilised; Control Levers and Performance Indicators. Control Levers and Performance Indicators have been explained in Chapter 3 as part of the proposed SA framework. In fact, the SA framework was conceived based on Table 14, and this was mentioned in Chapter 3 without going into the literature. The authors of each study in Table 14 are interested in the effects of the Control Levers on the Performance Indicators of the system. RES vary in the composition of their components which includes energy sources and storages. All the studies in Table 14 model RES containing PV with the exception of one which models battery only [264]. The systems combine PV with grid, battery, wind turbine and heat pump in different configurations. There is a study that even has the system configuration as a control lever [259].

Most of the reviewed studies are based on simulation models with the exceptions being financial models [254], [255]. In some cases, simulation optimisation is carried out which utilises the simulation model, for instance in determining the optimal battery size [252], [256] or optimal energy management strategy [253]. Lifecycle Analyses (LCA) have also been carried out together with the simulation [258], [260], [263]. Whilst most of the simulations are deterministic (a few studies introduced some stochasticity in the load profile), some studies have carried out sensitivity analysis to quantify the impact of uncertainty in the simulation [252], [254], [260]–[265]. The simulation models are used to model the operations of the RES, then the output is used to calculate the performance of the system in terms of the Performance

Indicators. In some cases, optimisation or sensitivity analysis are also carried out with the simulation model.

A variety of tools have been used in the literature as listed in Table 14, however they are not similarly accessible to potential users of the models due to certain barriers. Accessibility refers to the ability to understand a model (not the results of analysis using the model), or to create a model using the tool. Accessibility can be understood in terms of the skills barrier to be overcome before understanding or creating a model using the tool. Another barrier is financial barrier which is due to the cost of the tool. Financial barrier has been recognised in [264], however no recognition of skills barrier was found in the literature.

Meanwhile, some studies have not disclosed the tools they used, especially when they provide the mathematical equations that describe the model; in which case a number of tools can be used to run the equations. Some studies utilised multiple tools, including using some tools to generate input to the models, for example: using RETScreen for solar and wind data [257]; MATLAB for generating synthetic load profile [264] and PVGIS for 'pre-sizing' [266].

Each model in Table 14 has many input variables, however, the few listed as Control Levers are those that are highlighted by respective authors as being significant to the aims of the studies, as mentioned earlier. For example in [252]: different tariffs are included in the model to address a gap in the literature; technical and economic indicators were compared in scenarios with and without battery in the energy system; FiT (Feed in Tariffs) and other subsidies were included in the calculation of economic performance, and effort was made to model uncertainties in the model. Another example from [253] is that the study aimed to investigate the effects of battery degradation, energy management strategy, tariff, load profile and PV generation profile, on the Performance Indicators.

Many studies simulated PV generation based on weather variables, but it is not clear whether load profiles were simulated as well. In contrast, some studies provided load profiles and PV generation profiles as exogenous inputs, with studies taking different approaches. For load profiles, real load profile was used [267], or a 'representative' but real load profile was used [253], or a 'typical' load profile [257], or household with particular properties [259], or an estimation was carried out using monthly consumption [254] or synthetic profile was generated from real data [256], [264]. As for generating PV profile, real data were used [253], or machine learning technique was used to generate synthetic profile [256] or PV capacity was specified [257], [259].

Based on the literature surveyed, the RES are assessed for performance in three dimensions which are the technical, economic and environmental dimensions. The variety of Performance Indicators have been captured in Table 14 and some have been found to be more popular than others. Popular technical indicators include Self Consumption Rate (SCR) and Self Sufficiency Rate (SSR also known as autarky rate), while avoided greenhouse gas emission (CO_2, CO, NO_x, etc.) is the most utilised environmental indicator. Only six studies [251], [258], [260], [261], [263], [264] in the surveyed literature calculated environmental indicators, whereas all studies calculated economic indicators. The most utilised economic indicators include Payback Period (PBP), Levelised Cost of Electricity/Energy (LCOE), Net Present Value (NPV) and Internal Rate of Return (IRR). Whilst the equations for these indicators may not appear the same across the studies, they are essentially the same; some variables that appear missing in one equation are either irrelevant to the particular study or assumed to have values that make them inconsequential to be shown in the equation.

5.2.2 Gaps and Opportunities

Some gaps in the literature have been identified with regard to the Control Levers of the studies, and this has provided an opportunity to explore the system performance under some scenarios. Firstly, households of different sizes were not compared. Secondly, flat tariffs have not been compared with ToU tariffs, for both buying and selling. Thirdly, system operations strategies have not been compared. Fourthly, consumer types have not been compared. Finally, effects of model features have not been analysed. These gaps will be explored in subsequent sections.

5.3 Methodology

5.3.1 Case-Study Aims

Before describing the case-study of this chapter using the SA framework (Chapter 3), some areas of focus will be specified based on the gaps in the literature. The study is concerned with two focus areas of decision-making concerning the real-system and model-features.

1. In the case of decision-making about the real-system, there are two aims:
    a. Investigate the sustainability impact of charging batteries overnight from the Grid.
    b. Investigate the sustainability impact of being a ‘smart consumer’ of electricity.
2. In the case of decision-making about model-features, there are also two aims:

a. Investigate the impact of modelling battery degradation on the results of sustainability assessment.
b. Investigate the impact of modelling non-linear conversion on the results of sustainability assessment.

5.3.2 Case-Study Design

To achieve the study aims, the SA framework for designing and describing a study will be used. The SA framework (Figure 11) has been explained in Chapter 3, which was conceived based on Table 14. The two steps to design a study using the SA framework are: define the purpose of the study; and identify required variables. Thereafter, the simulation is run and performance of the system is calculated. The case-study of this chapter has been described using the SA framework and illustrated in Figure 27. The two steps shall be used to describe Figure 27. There are three levels of details in Figure 27 identified by the different font sizes, from general to specific in descending order; the two smallest fonts describe this study specifically, whereas the largest font identifies the dimensions of the framework as found in Chapter 3.

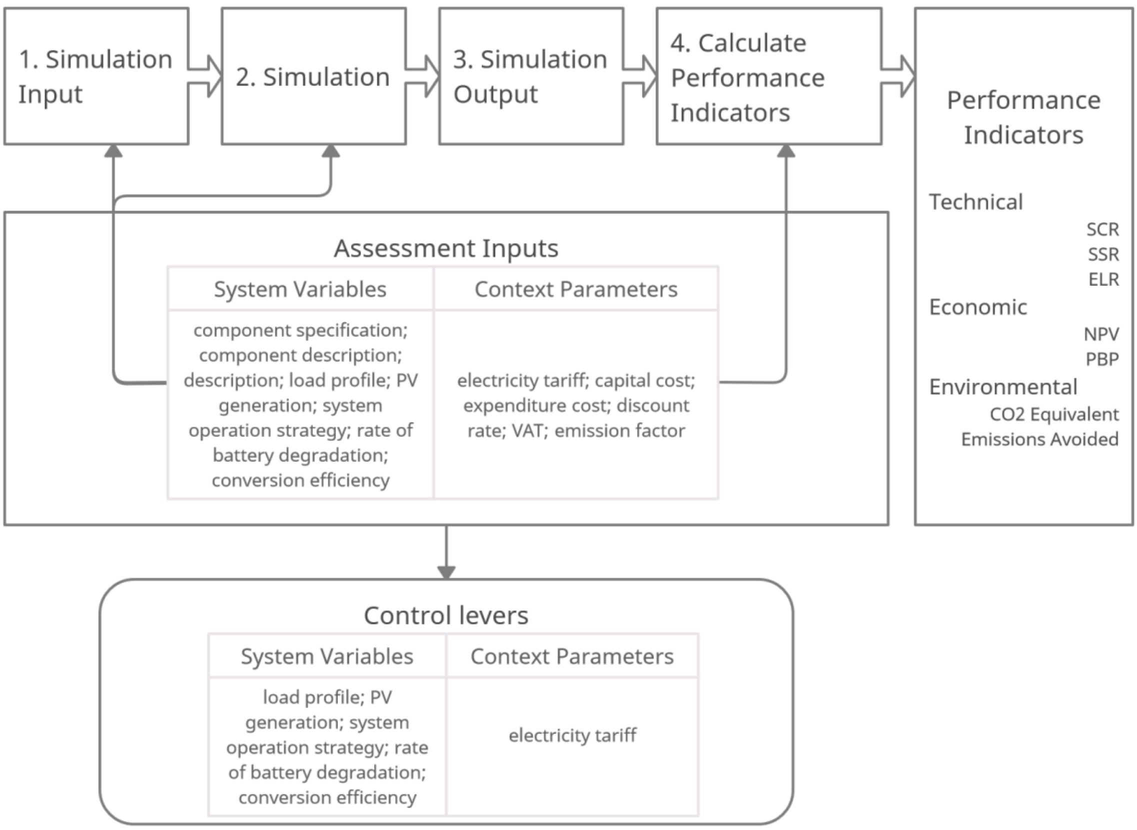

Figure 27 – Chapter 5 case-study design

The first step is to define the purpose of the study. The purpose of the study is defined in terms of Control Levers and Performance Indicators. The study compares the Performance Indicators of different scenarios of the RES, along the different dimensions of sustainability. The sustainability dimensions in this case-study are technical, economic and environmental. The scenarios defined by the Control Levers are discussed in section 5.3.3, while the Performance Indicators are discussed in section 5.3.4.

The second step is to identify the required variables. All the simulated system's variables can be listed under Assessment Inputs, however only those considered important are shown in Figure 27. System Variables refer to endogenous and exogenous variables used to create the bottom-up simulation, whereas Context Parameters are variables like tariff and capital cost which are used to calculate Performance Indicators. The exogenous System Variables are provided as input to simulation, the endogenous System Variables are provided as descriptions of the simulation model, then the Context Parameters and simulation output are used to calculate Performance Indicators. The exogenous and endogenous System Variables are discussed in Section 5.3.4, while the Context Parameters are discussed in Section 5.3.6.

The simulation process of the study has also been discussed in Chapter 3, and the simulation model utilised in this study was created and discussed in Chapter 4. However, the simulation model requires minor modification to achieve the aims of this study. The changes to the simulation model are discussed in Section 5.3.4. The outcome of the simulation process and Context Parameters are used to calculate the Performance Indicators.

5.3.3 Scenarios: Control Levers

The scenarios are defined by the Control Levers in Figure 27, which include System Variables (load profile, operation strategy, battery degradation and conversion efficiency) and Context Parameters (tariff). Each variable in Control Levers represents a dimension from which scenarios are created, though one dimension is a combination of two variables. The scenario dimensions are described in Table 15. Whilst four scenarios are expected based on Section 5.3.1, five scenario dimensions are provided in Table 15. This is because each of the four scenarios with specific focus areas will be explored along different numbers of residents. Each scenario is simulated at 1-minute resolution for the duration of a year.

Control Lever Variables	Scenario Dimension	Decision-making Focus Area
System operation strategy	Operation strategy of the residential energy system; specifically, battery charging rules.	Real-system
Electricity tariffs + System operation strategy	Consumer type that decides on operating strategy and tariff options.	
Battery degradation	Effects of modelling battery degradation.	Model-features
Conversion efficiency	Effects of modelling inverter conversion efficiency as constant or non-linear curve.	
Load profile	Number of residents living in the residence.	-

Table 15 – Dimensions of scenarios used for comparison

Based on the case-study aims and the focus areas in Table 15, there are two scenarios concerned with decision-making about the real-system, and they are compared along the dimensions of operating strategy and consumer type. There are also two scenarios concerned with decision-making about the modelling methodology, which compares scenarios with certain modelling features to scenarios without the features. The model-features are battery degradation and non-linear conversion efficiency. Therefore, the two real-system scenarios are of concern to applications of the model in the real-world, while the two model-features scenarios deal with methodological concerns for modellers. The number of residents (based on load profile) is an additional dimension that is evaluated for all the four aforementioned scenarios.

5.3.4 Performance Indicators

Table 16 shows the Performance Indicators that were selected to assess the performance of the system along three dimensions: technical, economic and environmental. The equations for the following Performance Indicators are provided after a brief explanation and adapted to the variables in the SD simulation model: SCR [261], SSR [261], Energy Loss Ratio, NPV [253], PBP [257], CO_2e Avoided. Energy Loss Ratio has not been found in the reviewed literature of techno-economic impact analysis, and this is a first use of it.

Technical	Economic	Environmental
SCR SSR	NPV PBP	CO_2e Avoided

Energy Loss Ratio		

Table 16 – Performance measures used in this paper

The equations of the Performance Indicators are provided in *Eq. 5.1 to Eq. 5.6*, the equation symbols are described in Table 17. SCR (Self Consumption Rate) is the proportion of PV power produced which is used (see *Eq. 5.1*). SSR (Self Sufficiency Rate) is the proportion of the load demand which is served by power produced from the PV panels (see *Eq. 5.2*). Energy Loss Ratio measures the fraction of energy lost during conversion between AC and DC power (see *Eq. 5.3)*. Energy Loss Ratio is important to measure in this model because of the non-linear energy conversion, which is less predictable compared to constant energy conversion that is prevalent in the literature. With a constant energy conversion, the Energy Loss Ratio is simply the percentage loss during conversion and so can be calculated before or after the simulation without measuring the actual energy lost. A high Energy Loss Ratio should motivate DC-DC connection between PV and battery, as well as possibly setting a threshold below which there is too much loss to use stored energy, and consider using the Grid instead. It may also be worth finding out how much of the SCR is affected by losses.

A simple PBP (Payback Period) is the duration it takes for the net revenue generated and saved by the system to equal the capital investment, whereas a discounted PBP adjusts for the time value of money. A simple PBP is used in this case-study (see *Eq. 5.4)*. NPV (Net Present Value) refers to the monetary value, at a particular time in the system's lifetime, of the system by subtracting the capital investment from net revenue generated and saved by the system (see *Eq. 5.5)*. NPV assesses the profitability of the system at a time in the future, but in today's monetary value. CO_2e Avoided estimates the greenhouse gas (GHG) emissions avoided by generating power from renewable sources (PV), in mass (g) of CO_2 equivalent. To calculate CO_2e Avoided, the fraction of electricity sources that emit GHG is accounted for, as well as the emission factor used to convert electric energy into equivalent mass of CO_2 (see *Eq. 5.6)*. In this case study, unlike most of the literature, energy losses are accounted for in the calculation of CO_2e Avoided.

$$SCR = \frac{\sum_{t=1}^{n}\left(P_{PVDirect} + P_{PVCharging}\right) \cdot \Delta t}{\sum_{t=1}^{n} P_{PVProduced} \cdot \Delta t}$$ *Eq. 5.1*

$$SSR = \frac{\sum_{t=1}^{n} \left(P_{PVDirect} + P_{PVDischarging}\right) \cdot \Delta t}{\sum_{t=1}^{n} P_{Demand} \cdot \Delta t}$$ *Eq. 5.2*

$$Energy\ Loss\ Ratio = \frac{\sum_{t=1}^{n} (P_{PV2AC} + P_{AC2Batt} + P_{Batt2AC}) \cdot \Delta t}{\sum_{t=1}^{n} P_{PVProduced} \cdot \Delta t}$$ *Eq. 5.3*

$$PBP = \frac{C_{Inv}}{R_{AnnualNet}}$$ *Eq. 5.4*

$$NPV = -C_{Inv} + \sum_{t=1}^{n} \frac{R_t}{(1+d)^t} \cdot \Delta t$$ *Eq. 5.5*

$$CO_2e\ Avoided = \sum_{t=1}^{n} \left(P_{PVDirect} + P_{PVDischarging} + P_{PVExport}\right) \times F_{CO2e} \times F_{GHGFuel} \cdot \Delta t$$ *Eq. 5.6*

Symbol	Description
t	Simulation time-step
n	Total simulation time-steps
P_{PVLoad}	Power produced from PV which goes to service load directly
$P_{PVCharging}$	Power produced from PV which goes to charge the battery
$P_{PVDischarging}$	Power produced from PV which is discharged from the battery after charging
$P_{PVProduced}$	Total power produced from PV
P_{Demand}	Load demand of the residence
P_{Import}	Power imported into the residence
P_{Export}	Power exported from the residence
$Max_n\ (P_{Import})$	Maximum imported power at time-step n
$Max_n\ (P_{Export})$	Maximum exported power at time-step n

P_{PV2AC}	Non-linear power loss converting from DC to AC; PV generation to mains
$P_{AC2Batt}$	Non-linear power loss converting from AC to DC; mains to battery
$P_{Batt2AC}$	Non-linear power loss converting from DC to AC; battery to mains
C_{Inv}	Initial capital investment for the residential energy system
$R_{AnnualNet}$	Net revenue per annum: revenue generated or saved minus maintenance cost
R_t	Net revenue per time
d	Discount rate
F_{CO2e}	Emissions factor for carbon dioxide
$F_{GHGFuel}$	Fraction of fuels used for electricity generation which emit GHG

Table 17 – Mathematical symbols

Whereas Performance Indicators from the literature are typically calculated at the end of a simulation, all Performance Indicators in this case-study are calculated at every step of the simulation. As for indicators that require variables that have units measured per annum, the per annum value is estimated based on data available up to the time using algebraic substitution. Therefore, the behaviour of the indicators can be visualised across time. A benefit of visualising the behaviour of indicators include insight into how the behaviour varies in different scenarios, as well as how much data is required before the indicators converge on their long-term value. Furthermore, the behaviour can be used in estimating a future value of Performance Indicators, and this is discussed in the next section.

5.3.5 System Variables

The models in this chapter are based on the SD model from Chapter 4. The Energy Management System (EMS) and non-linear conversion are the same as the validated model created in Chapter 4. Unlike the validated model, input like load profile and generated PV are not coming from measured data (Project SENSIBLE), but from a synthetic residential load generator, which also has a PV generation component. The sizes of the PV panels, inverter and battery were obtained from documents detailing the plans of project SENSIBLE which did not distinguish between household sizes. During the implementation of SENSIBLE, the sizes of PV panels had to be changed to accommodate other limitations like available space on roofs. However, the details of these changes were not accessible. In this case-study, the planned sizes were used across all houses, regardless of the number of occupants so that as many variables as possible remain the same across the scenarios with different number of occupants. In other words, the sizes of PV panels, inverter and battery are control variables when comparing the scenarios. Furthermore, the model has been modified to include battery degradation. Since the endogenous system variables (system components) have been discussed in Chapter 4, only some of the exogenous variables (system inputs) will be discussed in this section; specifically load profile, PV generation and battery degradation rate.

5.3.5.1 *Load Profile*

The input load profile is generated by the CREST (Centre for Renewable Energy Systems Technology) Demand Model of the University of Loughborough [208] which is freely available to generate load profile for a 24 hour period. It is a well validated synthetic demand model with high-resolution (1-minute intervals) which generates load profiles based on active occupancy in a residence and activity profile of the occupants. The active occupancy and activity profiles are derived probabilistically from the UK 2000 Time Use Survey (TUS) [268]. Other parameters of the model are specified in the model, including: number of residents; weekday or weekend; month of the year and appliances in the residence. Power requirements of appliances is based on data from sources like the UK Market Transformation Programme [269] and the UK Department of Energy and Climate Change [270], and there is an option to randomly assign appliances to a residence or specify manually.

A synthetic load profile has an advantage over a real load profile in the context of this study, which is that it is significantly less expensive to generate data for many days. The main limitation is that since it is driven by probability distribution, its output depends on the historic data of the population from which its probability distribution was derived. The population could be of a single (or few) residences over a long period of time, or of many residences over a short period of time; the former is more statistically representative of the single (or few) residences over time, whereas the latter is more representative of a larger set of residences within a short period. The CREST model is the latter; thousands of residences covering a single day which may be a weekday or a weekend. The most representative of a real residential population depends on whether there is higher variance across time (per residence) or across residences (per time); the most representative is the one that captures the higher variance in its probability distribution. Therefore, if there is higher variance across time, a synthetic load profile that represents many residences is more likely to be a better representative for policy about a real population than a synthetic load profile based on a single (or few) residences for a longer period of time.

Along the scenario dimension for number of residents, five types of residences have been specified, each with a different number of residents (one to five), and load profile was generated for a year. To address the limitation of the model which can only generates load profile for a day (1440 minutes), an automation script was created using Python to automate the creation of load profile for 365 consecutive days (525,600 minutes) that represent weekdays and weekends in a week. For each residence, the same occupancy is used for weekdays and another for weekends, for the year. To aid comparison among the residences, the same set of appliances are used for all the residences.

5.3.5.2 *PV Generation Profile*

There is a sub-model for PV generation in the CREST Demand Model [208], which simulates a synthetic PV profile based on irradiance data and PV parameters. The irradiance data comes from the CREST irradiance database. Some of the parameters that can be specified in the model include: geographical parameters; day of the year; start day of a season (summer); panel position parameters; panel area and panel efficiency. Therefore, to simulate the PV generation of any PV available for purchase, given the other parameters, the panel area and efficiency were specified in the model. Similar to the load profile, the generated PV profile is high resolution (1 minute). The PV profile was generated via a Python script for everyday of the year per residence, corresponding to the days of load profile.

5.3.5.3 *Battery Degradation Rate*

The lithium ion battery degradation rate was simulated based on data from a DST (Dynamic Stress Test) which resulted in a plot of Charge Capacity Retention against number of charge cycles for varying charge-discharge bandwidth (at 20 degrees Celsius) [271]. Therefore, given the number of charge-discharge cycles, the rate of degradation (slope) can be estimated using a linear regression for a particular charge-discharge cycle. The specification of the modelled battery shows that the battery can exceed 6000 cycles with a charge-discharge bandwidth of 100-10% at 25 degrees, and can last over 10 years. Observing the SD simulation output, the battery cycles daily regardless of the number of residents however, what changes is the charge-discharge bandwidth; more residents result in less bandwidth and lower upper bound. This makes sense because daily intermittence from the PV leads to charging during the day while use of battery at night leads to discharging, and having more residents would lead to more consumption from the battery, as well as lower maximum charge (especially if there is an occupant during the day). Table 18 shows the assigned bandwidth and estimated slope for each number of residents, which is based on [271] with different charge-discharge bandwidths.

Number of Residents	Charge-Discharge Bandwidth	Rate of degradation
1	50% (100-50%)	-3.75×10^{-3}
2	50% (75-25%)	-2.50×10^{-3}
3	50% (75-25%)	-2.50×10^{-3}
4	30% (75-45%)	-1.67×10^{-3}
5	30% (75-45%)	-1.67×10^{-3}

Table 18 – Bandwidth of charge-discharge cycles and rate of battery degradation used in the simulation model for residences having a different number of residents

5.3.6 Context Parameters

The Context Parameters used to calibrate the model are listed in the Table 19 (capital costs), Table 20 (economic parameters), and Table 21 (technical parameters) with relevant details. Context Parameters relevant to the environmental performance of the system can be found under economic parameters because they reflect the state of the electric power industry.

Cost Item	Product	Capital cost (£)	VAT Included (£)	Source
Battery	LG Chem RESU 6.4 EX	2,819	3,383	[272]
Battery Inverter	SMA Sunny Island 4.4M-12	2,258	2,710	[273]
	2.08kW Perlight PV Kit – 260w Poly Panel	1,395	1,674	[274]
PV Panels	Perlight PLM 260PB-60			
PV Inverter	Growatt 2000S Mini– Single Tracker – Single Phase Inverter			
PV Meter	Single Phase Generation Meter			
Transportation and Installation cost		500	500	-
Total			8,267	

Table 19 – Capital costs

Parameter	Value	Comment	Source
Discount rate (Annual)	-0.25%	It was 2.5% for many years but reduced to -0.75% in 2017, and the new rate is -0.25 starting 5th Aug 2019. A negative discount rate means that the present value is lower than the future value.	[275]
Operational and maintenance cost (Annual)	1%	Percentage of initial capital, but mainly for PV and battery because inverters hardly require maintenance. The cost varies between 1-2% but the inverters cost about 40% of the capital. Therefore, 1% of initial capital seems reasonable, as assumed in other studies in the literature.	-
VAT rate (Annual)	20%	-	[276]
Buying Tariff 1	18.3 p per kWh	Based on the single rate tariff for electricity offered by British Gas as Green Future Mar2020	[277]
Buying Tariff 2	Variable	This is a Time of Use tariff for electricity offered by Green Energy UK as TIDE tariff with the following costs (weekdays): 23:00 – 06:00 4.9 p 06:00 – 16:00 11.9 p 16:00 – 19:00 19.9 p 19:00 – 23:00 11.9 p	[278]
Selling Tariff 1	3.2 p	Smart Export Guarantee (SEG) is an obligation on electricity suppliers to buy electricity exported to the grid. The rate is the SEG tariff offered by British Gas.	[279]
Buying Tariff 2	0.2x	Where x is Buying Tariff 2. Estimated at 20% of Buying Tariff 2 at any time of the day based	-

		on comparing other buying and selling tariffs that do not vary through the day.	
Fraction of fuel with emission used for electricity generation	37%	This is the summation of fractional contributions of natural gas, coal and "other fuels" according to the UK 2020 quarterly report on electricity generation mix.	[280]
Emissions Factor for kWh in CO_2e	0.20374 kg CO_2	This is the UK government's conversion factor for greenhouse gasses for 2020.	[281]

Table 20 – Economic and environmental parameters

PV Module	
Surface area	15 m2
Module efficiency	13%
Lifetime	25 years
PV Inverter	
Maximum DC input power	2.6 kW
Maximum AC output power	2 kW
Conversion Efficiency (DC to AC)	non-linear
Lifetime	25 years
Battery	
Battery Capacity	6.4 kWh
Depth of Discharge	90%
Battery roundtrip efficiency	95%
Battery degradation rate	See section 5.3.5.3
Rated DC Charging Power	3.6 kW
Lifetime	10 years (minimum)
Battery Inverter	
Rated Input AC Power	3.3 kW

Rated Output AC Power	3.3 kW
Conversion Efficiency (DC to AC)	non-linear
Conversion Efficiency (AC to DC)	non-linear
Lifetime	10 years (warranty)
PV installation	
Latitude	52.8 degrees 0.92 radians
Longitude	-1.2 degrees -0.02 radians
Day of the year that summer-time starts	87
Day of the year that summer-time ends	304
Slope of panel	0 degrees 0 radians
Azimuth of panel	0 degrees 0 radians
Solar incident angle on panel	102.35 degrees 1.78 radians

Table 21 – Technical parameters

5.3.7 Simulating for 10 years

This section discusses the challenges and compromises in simulating for 10 years. The typical lifetime of a battery is 10 years, and 25 years for PV panels (see Table 21). Simulation input data (load profile and PV profile) for 10 years have been generated, but there appears to be a memory limitation on Vensim PLE+ when the simulation steps exceed one million steps. Vensim PLE+ would crash when instructed to run the simulation for 10 years at 1-minute resolution, which is 5,256,000 time-steps. However, Vensim PLE+ is able to run the simulation for one year, which is 525,600 time-steps, but not two years, which is 1,051,200 time-steps. To get around this limitation of Vensim PLE+, two possible solutions were explored. It is possible to run for 10 years at 10-minute resolution, which is downsampling. Alternatively, statistical methods might be useful to estimate the performance of the simulation in 10 years given a 1-year simulation.

5.3.7.1 *Squeezing Time by Downsampling*

5.3.7.1.1 Downsampling

Downsampling is the process of reducing the resolution or frequency of a time series data from a higher resolution (e.g. minutes) to a lower resolution (e.g. hours). The original data is statistically summarised in the lower resolution, and this is typically by statistical mean. In the example of downsampling from minutes to hours, every hour, which represents a single data point in the downsampled data, summarises 60 minutes. Consequently, statistical mean flattens the original data because it would appear as if the downsampled variable remained the same for the duration of an hour. Whilst there are situations where downsampling does not lead to significant errors, it does in the situation of RES especially because some variables depend on the value of other variables exceeding a threshold, which is less likely to occur when the threshold is sufficiently large and all fluctuations have been flattened by downsampling. For example, Figure 28 and Figure 29 each compares one of the time series inputs to the simulation in the original resolution (1 minute) and the downsampled resolution (10 minutes), for a residence with 3 residents for a duration of 7 days. The higher resolution (1 minute) has more peaks in case of load demand; but the average power is the same for both resolutions as expected at 631 W. In the case of PV Generated, the difference is in fluctuation with the higher resolution going higher and lower; both have an average of 443 W. As expected, downsampling smoothens the plots.

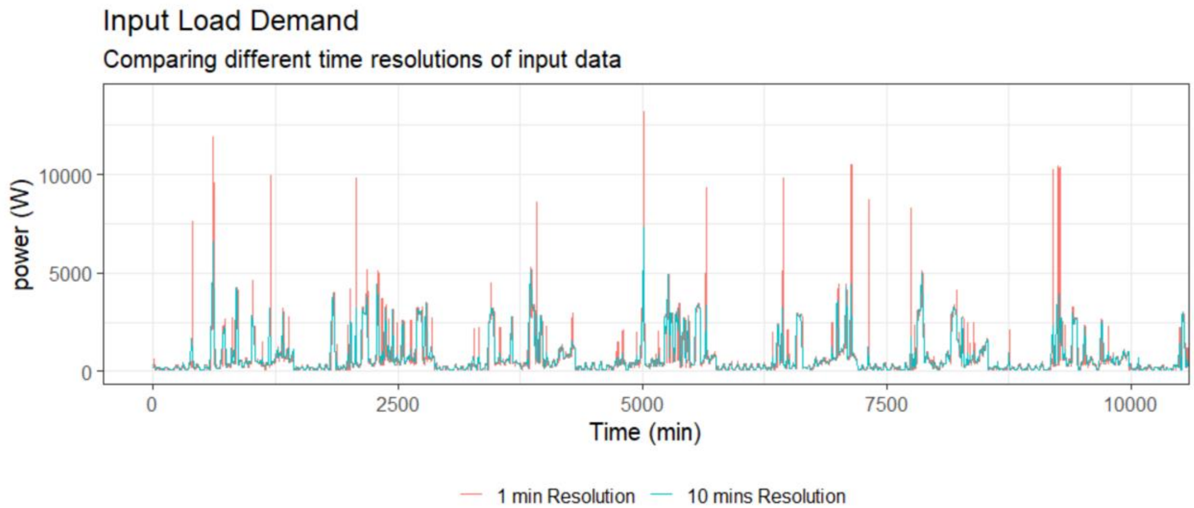

Figure 28 – Comparing the data of load demand at 1 minute resolution to its downsampled version at 10 minutes resolution, for the duration of 7 days.

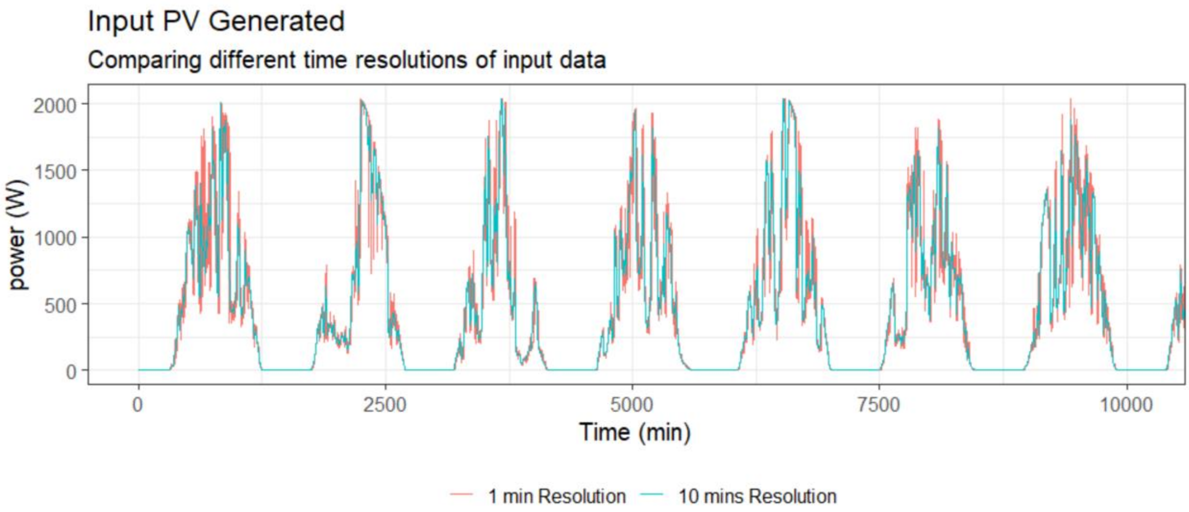

Figure 29 – Comparing the data of PV generated at 1 minute resolution to its downsampled version at 10 minutes resolution, for the duration of 7 days

5.3.7.1.2 Downsampling Error

A theory of downsampling error is presented: if the power imported depends on the threshold of load demand, for example exceeding 5000 W, then power will be imported significantly less when the load data is downsampled (10 minutes resolution) than when it is not downsampled. In the real system, the threshold is determined by the rated power of the inverter which would limit the amount of power discharged even if surplus energy is available in the battery, and therefore lead to importing power. Therefore, the downsampled data is less representative of the real system.

Consequently, when the output from a simulation is compared to output from a downsampled version of the same simulation, the difference is significant. Figure 30 shows the difference between variables in a simulation sampled at 1 minute resolution and a downsampled version of the same simulation at 10 minutes resolution, for the duration of a year. The comparison is made relative to the simulation of 1 minute resolution but plotted in absolute value, and the variables are compared across 5 scenarios defined by the number of residents in the residence.

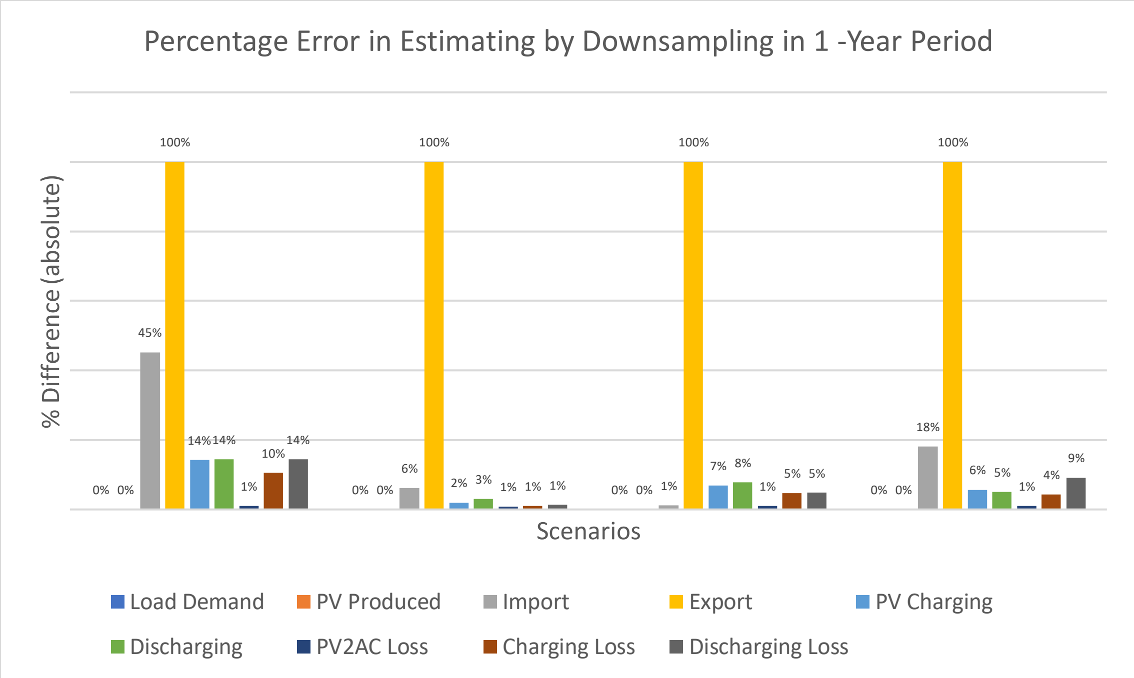

Figure 30 – Comparing the cumulative difference after 1 year between variables simulated at 1 minute and 10 minutes resolution

Based on Figure 30, the difference in Export and Import seems to be the largest, across the different scenarios, with Export almost being non-existent in the downsampled data. The suggested theory has been confirmed that the error is highest for variables that depend on a threshold (rated power) to have values at all; which are Import and Export.

Whilst downsampling from 1 minute to 10 minutes leads to less accurate representation of the system's behaviour, it should be noted that even the 1-minute data is a downsampled version of the actual behaviour of a real system which should operate on the resolution of seconds at least. Downsampling error from seconds (real world standard unit) to minutes (measurement, and simulation) has been discussed in Chapter 4.

5.3.7.2 *Using Statistical Methods*

5.3.7.2.1 Behaviour of indicators

Since the Performance Indicators are calculated at every time-step, their values over time can be plotted graphically, and the plots illustrate the behaviour of the indicator. Two broad types of behaviour have been discovered: converging behaviour and linear behaviour. An example of converging behaviour is shown in Figure 31, while linear behaviour is shown in Figure 32. Converging behaviour fluctuates widely for a period before stabilising, whereas linear behaviour exhibits linear growth or decay from the start of the simulation. Table 22 shows the

Performance Indicators and the type of behaviour they exhibit: SCR, SSR, PBP and Energy Loss Ratio have converging behaviour, while NPV and CO_2e Avoided have linear behaviour.

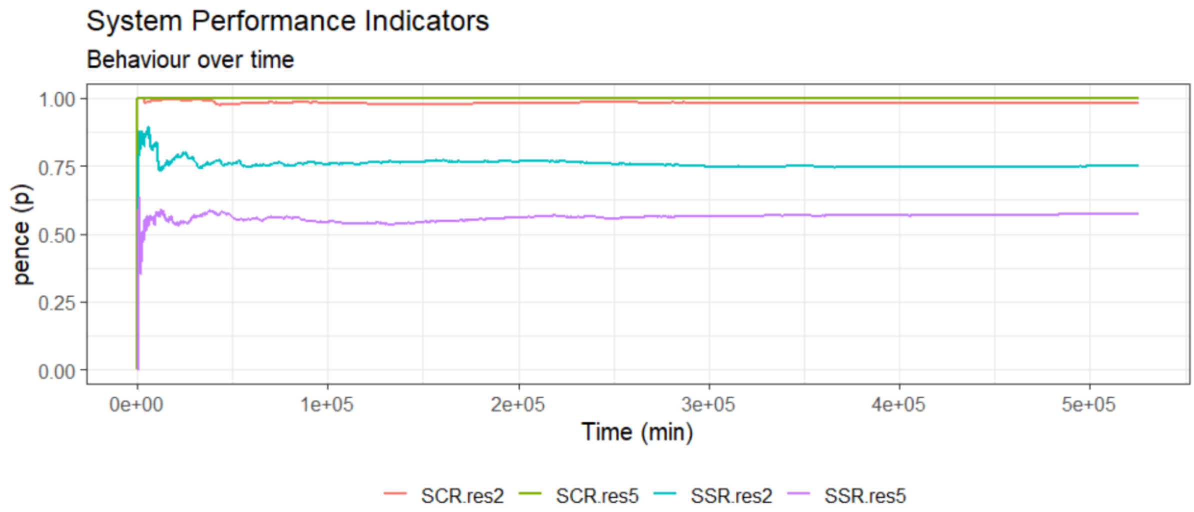

Figure 31 – Examples of system Performance Indicators (SCR and SSR) exhibiting converging behaviour for scenarios with 2 residents (res2) and 5 residents (res5)

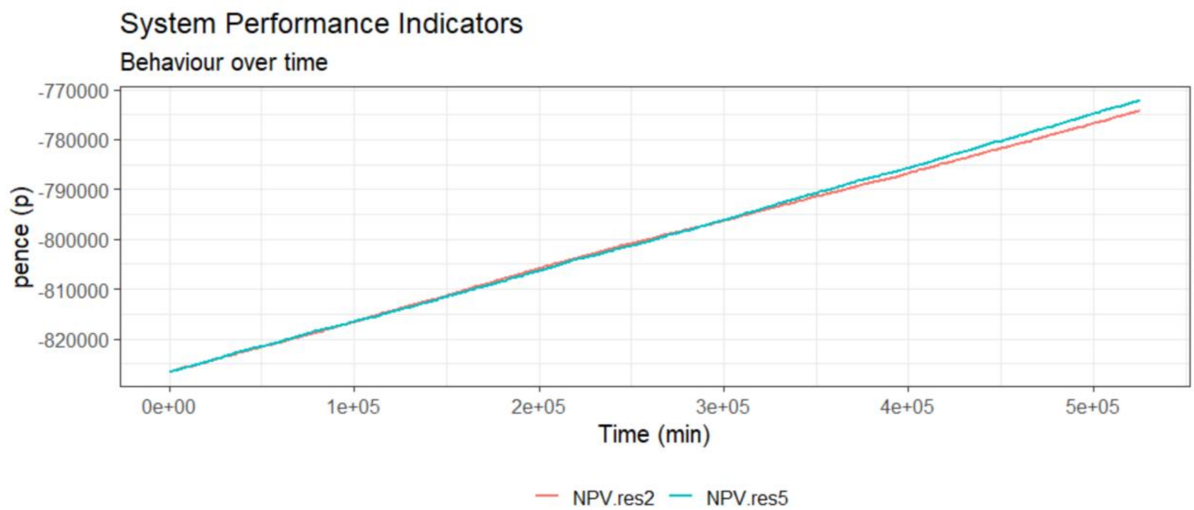

Figure 32 – Examples of system Performance Indicator (NPV) exhibiting linear behaviour for scenarios with 2 residents (res2) and 5 residents (res5)

Converging Behaviour	Linear Behaviour
SCR SSR Energy Loss Ratio PBP	NPV CO_2e Avoided

Table 22 – Classification of the Performance Indicators based on the behaviour they exhibit

The reason for the two behaviours can be attributed to the equations of the Performance Indicators (see *Eq. 5.1* to *Eq. 5.6)*. Equations that lead to converging behaviour are a division operation between two terms, where the denominator varies as simulation time progresses. On the other hand, equations that lead to linear behaviour are basically summations. The converging Performance Indicators (Figure 31) fluctuate in the beginning where the simulation time is so early that the calculation would be considered unreliable; the early times are the equivalent of when n is small in *Eq. 5.1* to *Eq. 5.3*. Using Figure 31 for example, which covers the duration of a year, calculating SSR at different points during the first month would be expected to vary more compared to calculating during the second or third months, and calculating at different points in the first week would vary even more drastically.

5.3.7.2.2 Regression, Mean and Error

There are at least two implications of identifying the behaviour of an indicator (over time). The first implication is that the value of the indicator could be estimated at a future time beyond the end of the simulation, using mean or linear regression for converging or linear indicators respectively. The second implication is related to the first, which is that simulations can be carried out for shorter periods and obtain reasonably accurate estimation. The accuracy of the estimation can be evaluated based on the statistical strength of the linear regression models in the case of linear indicators, and based on the variation of the values in the case of converging indicators.

Whilst the behaviour of the converging indicators appears linear after a while, using a linear regression to estimate future values could lead to impossible values. This was confirmed by estimating the future values of SCR and SSR which are ratios, but values greater than 1 were obtained. Therefore, linear regression will not be used to estimate the future performance of converging indicators. However, estimating using mean resulted in reasonable values that were less than 1.

Figure 33 shows the error in estimation for different indicators by plotting the percentage difference between indicators calculated from a 1-year simulation and the statistical estimation of the indicators at 1-year, based on a subset of the simulation data. Considering the high fluctuation of converging indicators, the earliest data points are not used to estimate the future value (using statistical mean). Instead, the indicator time-series was divided into five sequential and equal chunks, and the third chunk is used to estimate the indicator's value at the end of the fifth chunk. Thereafter, the difference between the estimated and simulated values is expressed as a percentage of the simulated value in Figure 33. A linear regression model is created for the indicators with linear behaviour and used to estimate the future value. The scenarios are made up of two tariffs (flat buying and selling prices, and Time of Use buying and selling prices which fluctuate according to time of the day) for each of the 5 types of residences.

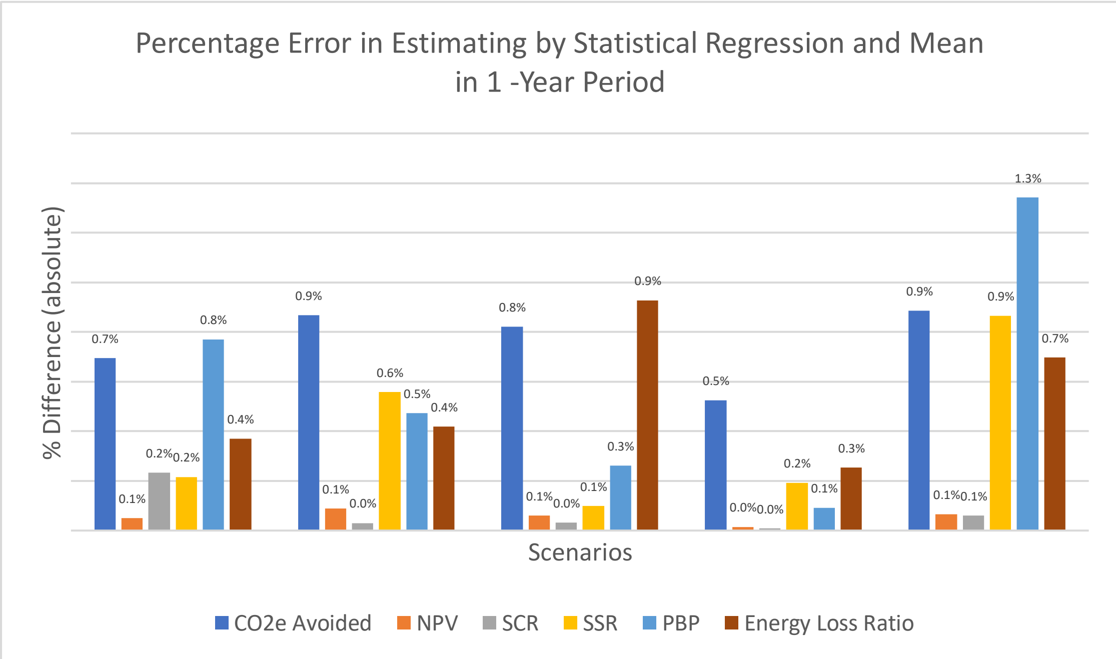

Figure 33 – Percentage difference between simulated performance and estimated performance for different scenarios. The scenarios are along two dimensions: number of residents and tariff type (flat or ToU).

Looking at Figure 33, all the differences in estimation fall below an absolute magnitude of 1% relative to the simulated value, except PBP which is just 1.3% in the scenario of 5 residents on flat tariff. The estimation was also ran for all the scenarios but with ToU tariff and the values were found to be identical to the scenarios with flat tariff except in the case of NPV and PBP; where the percentage difference was the same as flat tariff for NPV but varied to a high of 1.7% where it is 1.3% for flat tariff. This is because tariff is an economic parameter, NPV and PBP are the only economic indicators. The statistical quality of the linear regression models (for CO_2e Avoided and NPV) is very high with a P Value less than $2x10^{-16}$ for all the coefficients.

Since high resolution data provides higher accuracy especially in the case of RES(as shown in Section 5.3.7), and given the level of accuracy from estimation of simulated variables using linear regression models, then higher resolution simulations could be carried out for less time periods, and then values at a future time can be estimated.

5.3.7.3 *Choice between Downsampling and Statistical Methods*

Comparing the errors from downsampling (Figure 30) with statistical regression (Figure 33), the latter generates better results. Therefore, the statistical approach will be used subsequently to estimate Performance Indicators at 10 years, using a 1-year simulation. Caution should observed when estimating the indicators based on their behaviour. For indicators of converging behaviour, it has been noted that care should be taken to identify the time it begins to noticeably converge (i.e. fluctuations are minimal) so that the mean operation is not built on noisy data. As for indicators of linear behaviour, physical limits of the devices should be acknowledged e.g. battery or PV panel degradation. Since most batteries are expected to show significant degradation after 10 years, and PV panels usually have a lifetime of 25 years, caution should be taken when estimating system performance between 10 and 25 years, and no estimations should be carried out beyond 25 years for a system with PV.

5.4 Results and Discussions

5.4.1 Scenarios Real-System

Before comparing the main scenarios of interest for this case-study, the context will be set by exploring the trends in a base scenario. Thereafter, Performance Indicators of the RES are compared across different scenarios after 10 years of simulation time. The simulation is carried out at 1-minute resolution for a year and then Performance Indicators after 10 years was estimated as explained in Section 5.3.7.2. However, in this section, the first half of the simulated data (6 months) is not used in the estimation because Performance Indicators that exhibit converging behaviour fluctuate at early periods in the simulation (as discussed in Section 5.3.7.2), while Performance Indicators that exhibit linear behaviour behave consistently from beginning to end. Since using the second half of the data only does not affect linear behaviour, both converging behaviour and linear behaviour use the second half of the data for consistency in the analysis.

5.4.2 Base Scenarios as Background

The base scenarios for each type of residence have the following configurations: buying tariff 1, selling tariff 1 and operation strategy 1. The Performance Indicators for the base scenario can be found in Figure 34 – Figure 38. There appears to be a clear trend in all the indicators as the number of residents increase, especially if the scenario with 4 residents is excluded. NPV simulation of 1 year and estimation for 10 years is presented in Figure 34. Focusing on the 1-year simulation, with a capital investment of about £8200, about 4.6% of the initial cost would have been recovered after 1 year in the scenario with 1 resident (scenario 1), and 5.8% in the scenario with 5 residents (scenario 5). Therefore, the entire investment should be recovered after about 22 years for scenario 1, and 17 years for scenario 5, if NPV grows linearly. When compared to the 1-year simulation in Figure 35, PBP is estimated at about 23 years for scenario 1 and 18 years for scenario 5. Therefore, the simulated values of NPV and PBP (for 1-year simulation) differ within 1 year margin of error. A similar trend has been observed in the scenarios using the 10-years estimated values of NPV and PBP, but the margin of error increases to 3 years. However, NPV is consistently growing slightly faster than PBP in all the scenarios for both 1-year and 10-year durations.

The reason why NPV grows faster than PBP may be because the NPV equation is not actually linear but exponential because NPV accounts for annual discount rate, whereas the PBP formula is linear (simple PBP). If the discount rate is positive, NPV becomes a logistic growth (that is money is less valuable in the future compared to linear growth), whereas when the discount rate is negative, NPV becomes an exponential growth. In this study, the discount rate is negative (-0.25% in Table 10) and so exponential growth should be expected albeit faint because of the small magnitude. Nonetheless, it is possible that the linear regression model used to estimate the NPV at 10 years has modelled the slight exponential growth, and this might explain why it seems NPV is growing faster than PBP even after 10 years. Another way to confirm whether NPV is growing exponentially is by calculating the change after 1 year and multiplying that with 10 to get the change after 10 years. If the calculated value is less than the estimated value then the variable is exponential, otherwise it is linear if approximately the same. It was found that the values when multiplied by 10 (46% and 58%) are less than the estimated values using regression (53% and 66% respectively). On the other hand, the rate of growth of CO_2e Avoided is inconsistent across the residence types (see Figure 36); slightly more in some scenarios and slightly less in other scenarios.

SCR increases (see Figure 37), whereas SSR (see Figure 37) and Energy Loss Ratio decrease (see Figure 38) across the scenarios as the number of residents increase. It makes sense that as residents increase, more of the generated PV power will be consumed, having less of the excess which may be exported; hence increasing SCR. Simultaneously, the proportion of the load that is served by importing from the grid increases especially at night because less energy has been stored during the day; hence decreasing SSR. Consequently, Energy Loss Ratio decreases because less energy is stored in the battery and a significant source of energy loss is in charging and discharging.

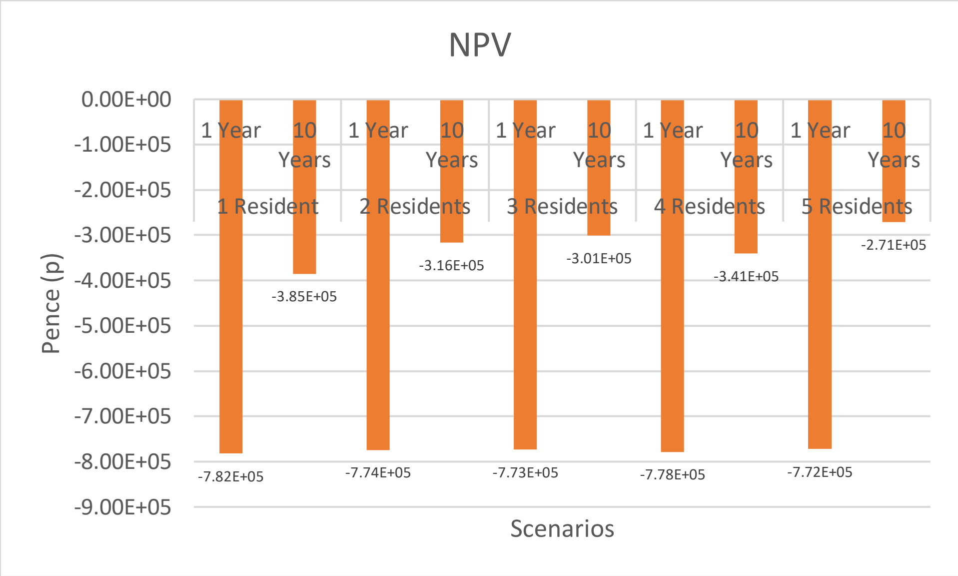

Figure 34 – NPV for base scenarios showing simulation at 1 year and estimation at 10 years

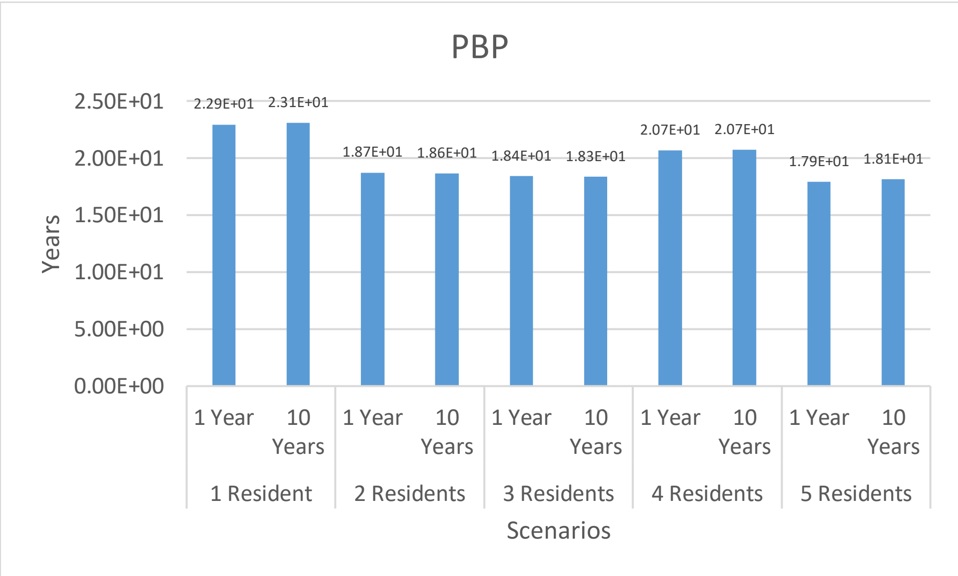

Figure 35 – PBP for base scenarios showing simulation at 1 year and estimation at 10 years

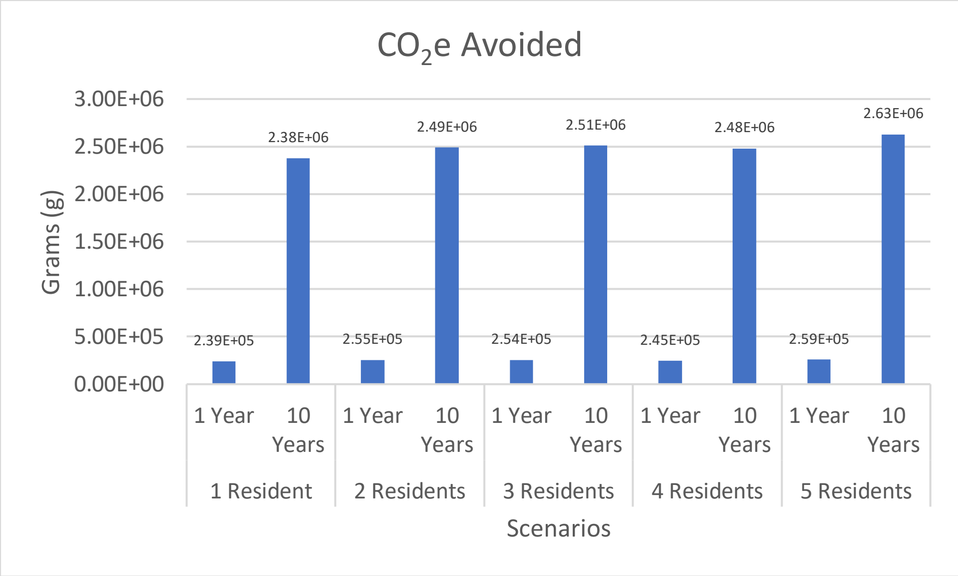

Figure 36 – CO_2e Avoided for base scenarios showing simulation at 1 year and estimation at 10 years

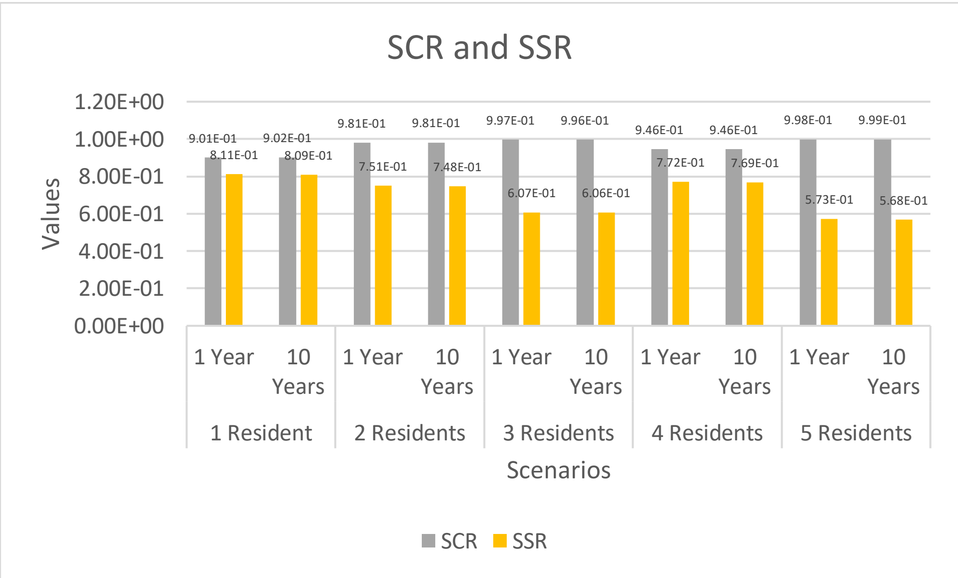

Figure 37 – SCR and SSR for base scenarios showing simulation at 1 year and estimation at 10 years

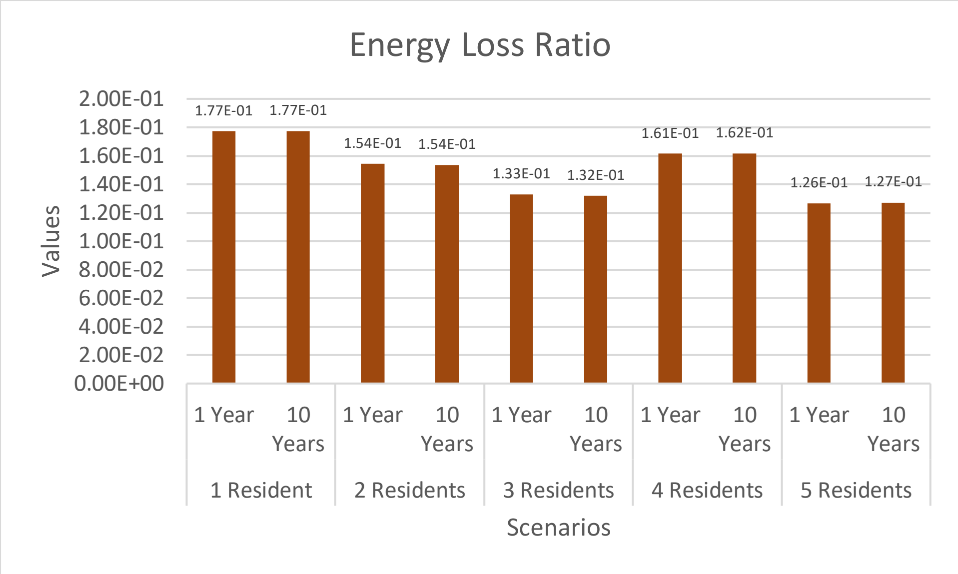

Figure 38 – Energy Loss Ratio for base scenarios showing simulation at 1 year and estimation at 10 years

5.4.2.1 *System Operation Strategies*

Two simple system operation strategies were explored. The first strategy (OS1) charges the battery with power generated from PV that is not used directly for Load Demand, and then discharges in the absence of PV and imports from the grid to supplement the battery. The second strategy (OS2) does what the first strategy does, but it also charges the battery to full charge overnight when the cost of power is least. Additionally, the tariff used for buying and selling energy in both OS1 and OS2 is a Time of Use (ToU) tariff which changes depending on the time of day. In the case of OS2, the formula for calculating the Performance Indicators was adjusted to reflect the fact that not all charge stored in the battery is from PV, and also that the battery contributes economically by price arbitrage. There were two adjustments made. First, discharging only applies to what has come from PV not grid, when calculating for all 3 types of Performance Indicators. Second, discharging what comes from the grid is used to account for the economic benefits (price arbitrage) of having a battery that stores cheap energy, and this benefit is added to the economic indicators. However, there was no need for adjustment to Energy Loss Ratio. Energy Loss Ratio, based on the equation, is relative to power generated from PV only; excluding power loss in storage and discharge of power sourced from the Grid.

The Performance Indicators in scenarios with OS1 and OS2 are compared after 10 years in Figure 39 to Figure 43. OS2 consistently outperforms OS1 economically (NPV in Figure 39 and PBP in Figure 40) and environmentally (CO_2 Avoided in Figure 41). Technically, OS1 performs better in SCR (see Figure 42) and SSR (see Figure 42), but OS2 performs better in Energy Loss Ratio (see Figure 43). Taking advantage of the cheap energy price at certain times offered by a ToU tariff could be economically beneficial as shown in OS2. On the other hand, increased reliance on the grid leads to poorer performance technically on SCR and SSR as shown in OS2. However, the reason why OS2 performs better in CO_2 Avoided and Energy Loss Ratio is related to increased reliance on the grid. In the case of Energy Loss Ratio, a fully charged battery during the day means excess power from the PV is sold to the grid without losing energy in conversion while charging and subsequently discharging. Due to the reduction in loss during discharging, CO_2 Avoided is higher because there is less contribution from battery discharge but instead goes straight to export. Therefore, the difference in magnitude between OS1 and OS2 for the different scenarios in CO_2 Avoided (see Figure 41) is proportional to the difference in Energy Loss Ratio (see Figure 43).

Therefore, even a simple battery operation strategy could improve the economic attractiveness of a RES; for example, by reducing the payback period by 25% with 5 residents; or increasing the NPV by 20% with 5 residents. Environmentally, CO_2 Avoided can be improved by 10% with 1 resident. Technically, Energy Loss Ratio can be improved by 53% with 1 resident, while SCR worsens by 44% with 1 resident, and SSR also worsens by 40% with 1 resident.

The difference in economic performance is mainly due to the price arbitrage which is enabled by the battery storage sub-system, because the tariff is the same for OS1 and OS2. Therefore, this economic improvement demonstrates the potential value that can be added by the battery storage subsystem which constitutes 75% of the capital investment.

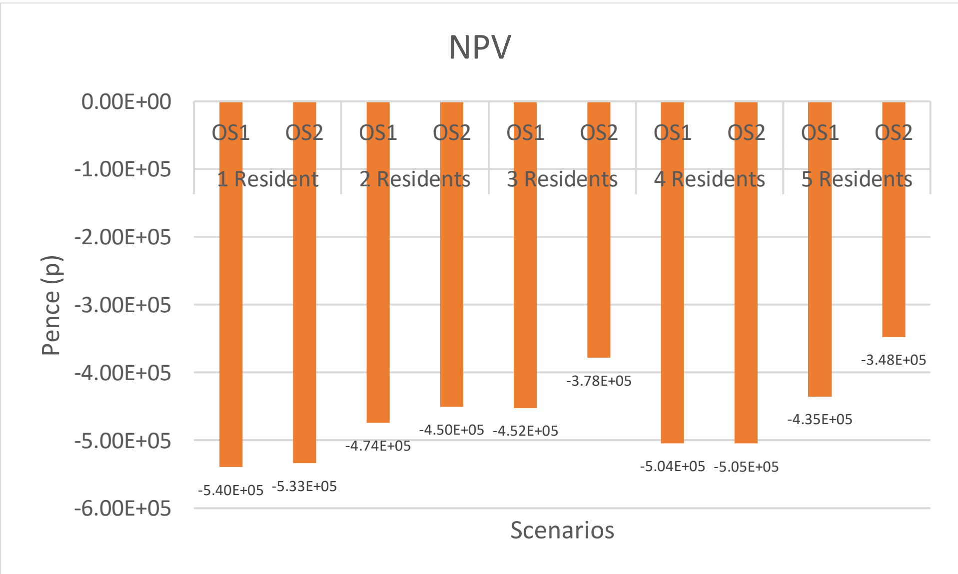

Figure 39 – Comparing NPV for two system operation strategies (OS1 and OS2) across different types of residences

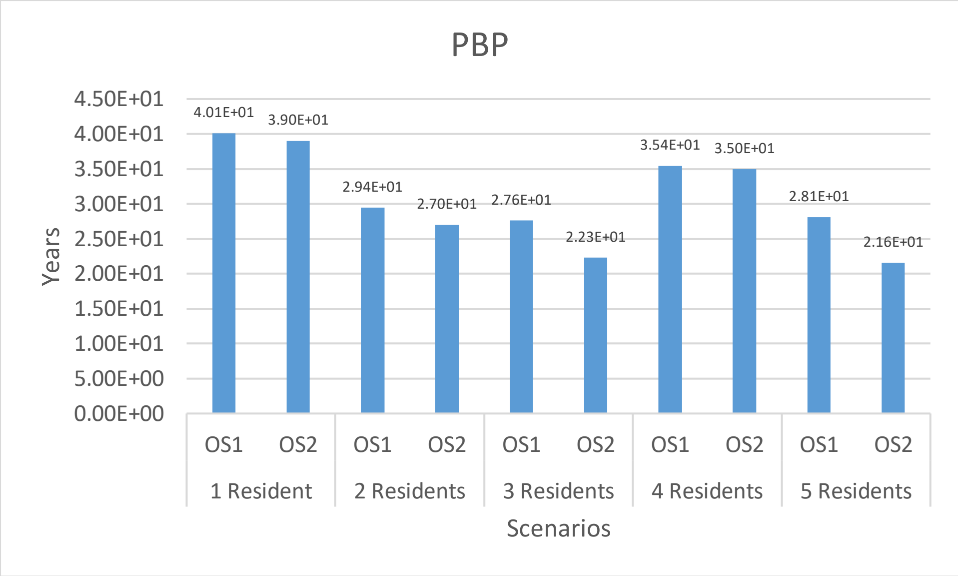

Figure 40 – Comparing PBP for two system operation strategies (OS1 and OS2) across different types of residences

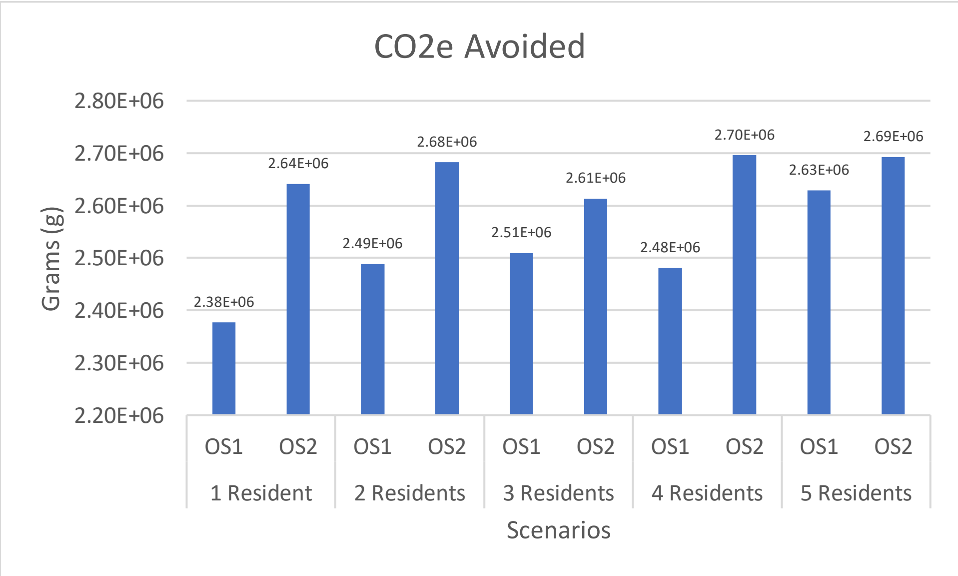

Figure 41 – Comparing CO_2e Avoided for two system operation strategies (OS1 and OS2) across different types of residences

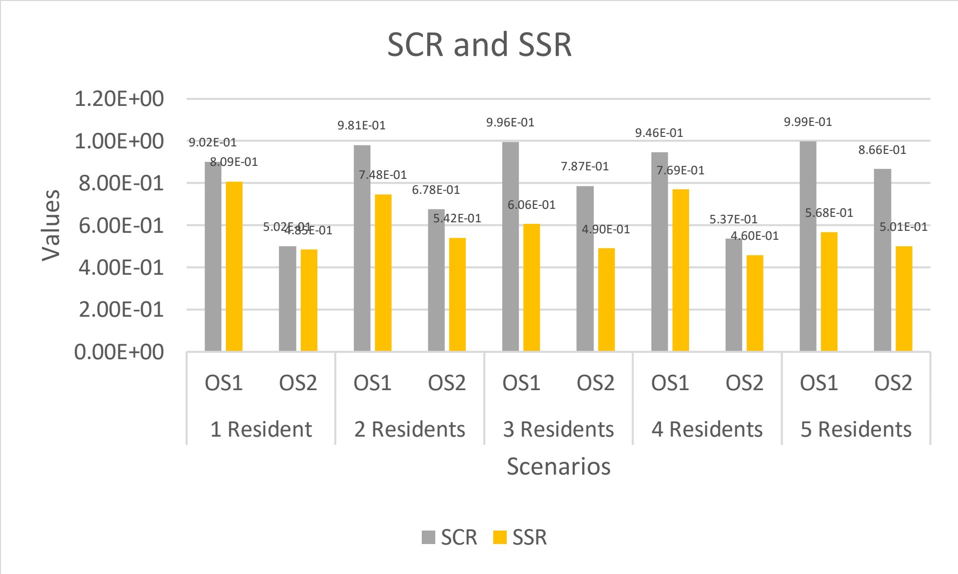

Figure 42 – Comparing SCR and SSR for two system operation strategies (OS1 and OS2) across different types of residences

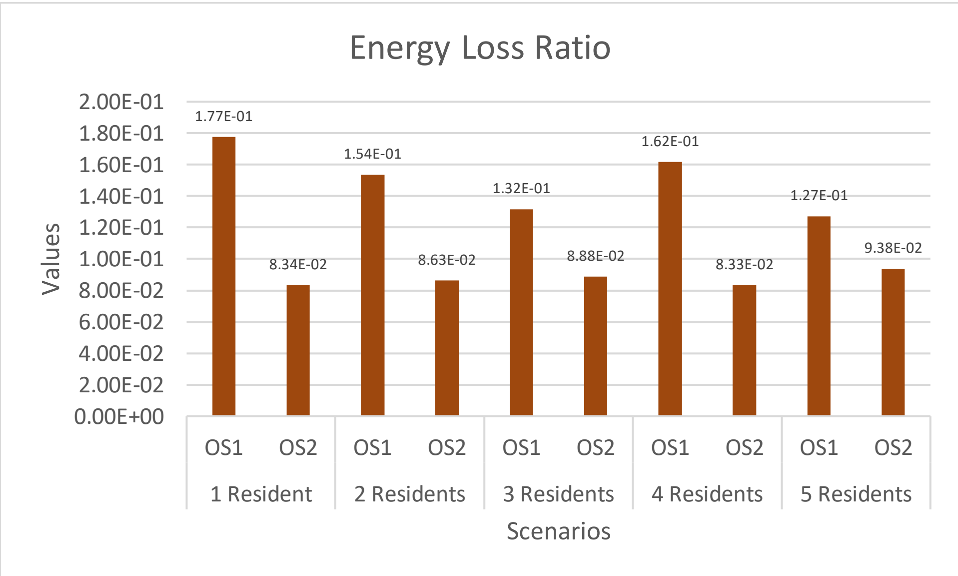

Figure 43 – Comparing Energy Loss Ratio for two system operation strategies (OS1 and OS2) across different types of residences

5.4.2.2 *Consumer Type*

Two types of residences were compared based on the behaviour type of consumers in each residence, who are mainly responsible for decisions about how to set up and operate the RES; named Type 1 and Type 2 consumer. Type 1 consumer is the one who goes with the default setup and does not put in extra effort to seek, or opt for, optimum performance; also known as the ‘regular’ consumer. Type 2 consumer refers to the one who seeks, or opts for, optimum setup of the RES; also known as the ‘smart’ consumer. In this scenario, Type 1 consumer goes for a flat buying and selling tariff and has the battery operate on OS1, whereas the Type 2 consumer goes for ToU tariff for buying and selling as well as having their battery operate on OS2.

The Performance Indicators in scenarios with Type 1 and Type 2 are compared after 10 years in Figure 44 to Figure 48. The scenario with 1 resident consistently shows the largest difference in comparison across the different number of residents, but the comparison of better performance is the same in all the other scenarios with a different number of residents. Type 1 consumer outperforms Type 2 consumer economically; in the scenarios of 1 resident with NPV (see Figure 44) and PBP (see Figure 45) of about -£3850 and 23 years, which is better than about -£5330 and 39 years respectively. Environmentally (see Figure 46), Type 2 outperforms Type 1; in the scenario of 1 resident with about 2640 $kgCO_2e$ and 2380 $kgCO_2e$ respectively. Technically, Type 1 performs better than Type 2 in SCR (see Figure 47) and SSR (see Figure 47) but not in Energy Loss Ratio (see Figure 48): in the scenario with 1 resident, Type 1 has SCR of about 0.9 whereas Type 2 is 0.5; Type 1 has SSR of about 0.8 whereas Type 2 is 0.48; and Type 1 has Energy Loss Ratio of 0.18 whereas Type 2 is 0.08.

Therefore, the comparison above shows that simple and default approaches to operating the RES could outperform a more sophisticated strategy economically and technically, even while underperforming environmentally. The compared scenarios are specific and therefore the outcome cannot be generalised and assessment must be made on case-by-case basis. Nonetheless, this is a significant finding because it does not seem intuitive to conclude that a simpler operation strategy would outperform a more sophisticated approach in most of the indicators. It is also interesting that the result is in spite of OS1 appearing to be the more expensive tariff: for buying, OS1 is a flat 18.3 p per kWh whereas OS2 is 11.9 p per kWh for 14 hours a day and 19.9 p per kWh for 3 hours; for selling, OS1 is flat at 3.2 p per kWh whereas OS2 is 20% of the buying price which is 2.4 p for 14 hours and 4 p for 3 hours. See Table 10 for details of the tariff.

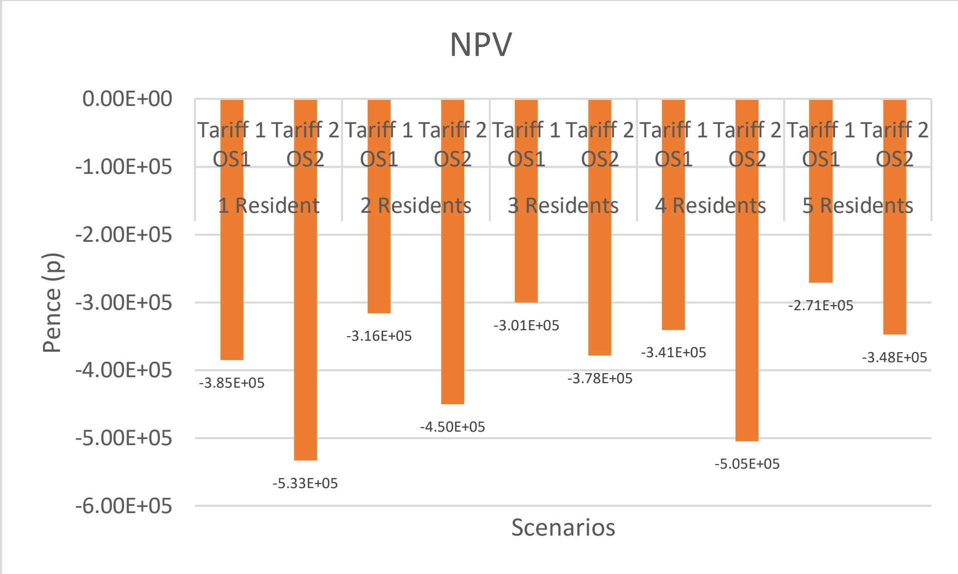

Figure 44 – Comparing NPV for two types of Resident Behaviour (Type 1 and Type 2) across different types of residences

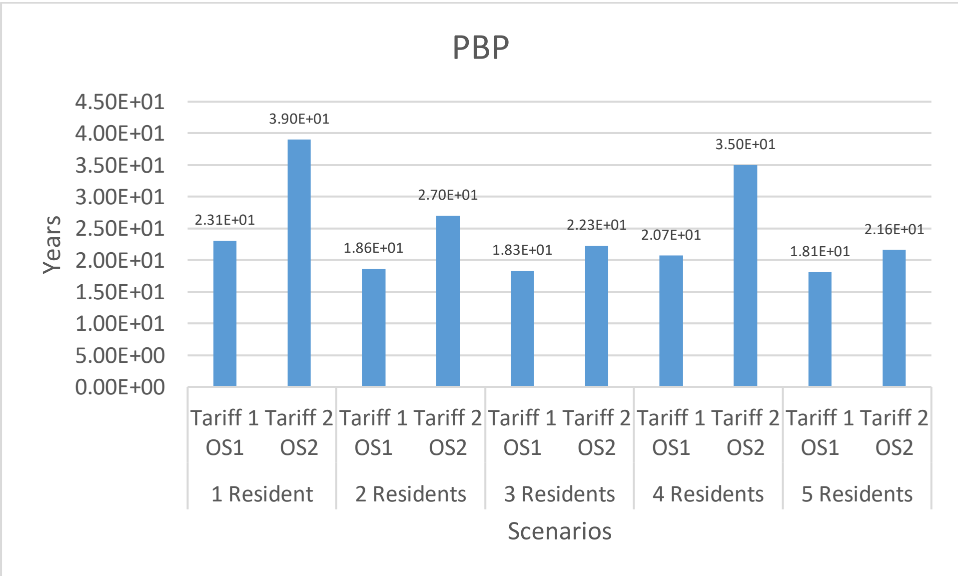

Figure 45 – Comparing PBP for two types of Resident Behaviour (Type 1 and Type 2) across different types of residences

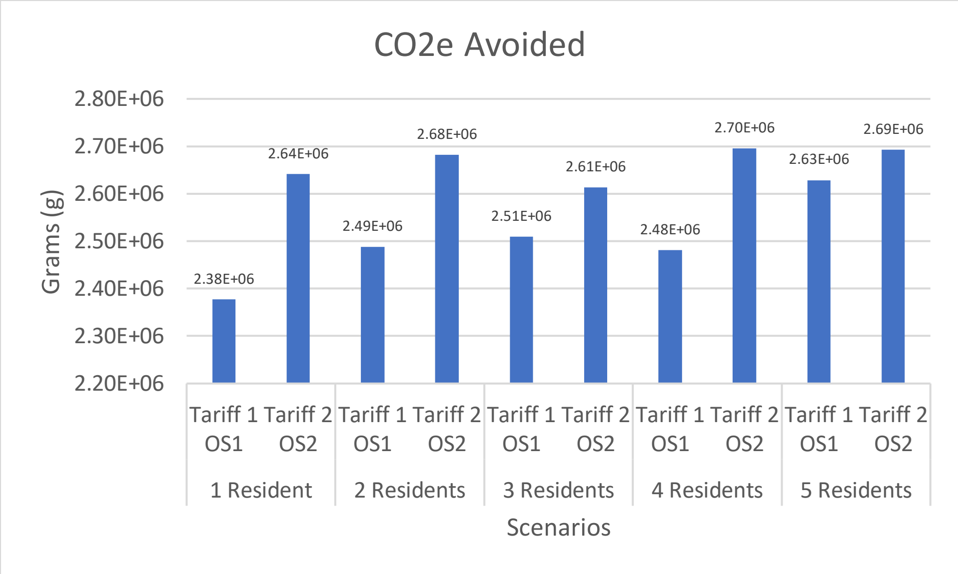

Figure 46 – Comparing CO_2e Avoided for two types of Resident Behaviour (Type 1 and Type 2) across different types of residences

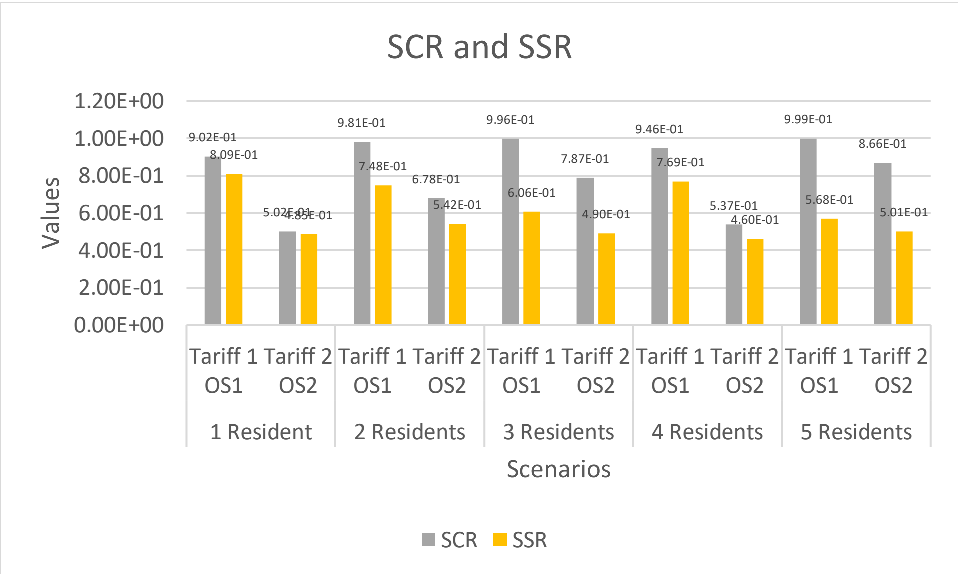

Figure 47 – Comparing SCR and SSR for two types of Resident Behaviour (Type 1 and Type 2) across different types of residences

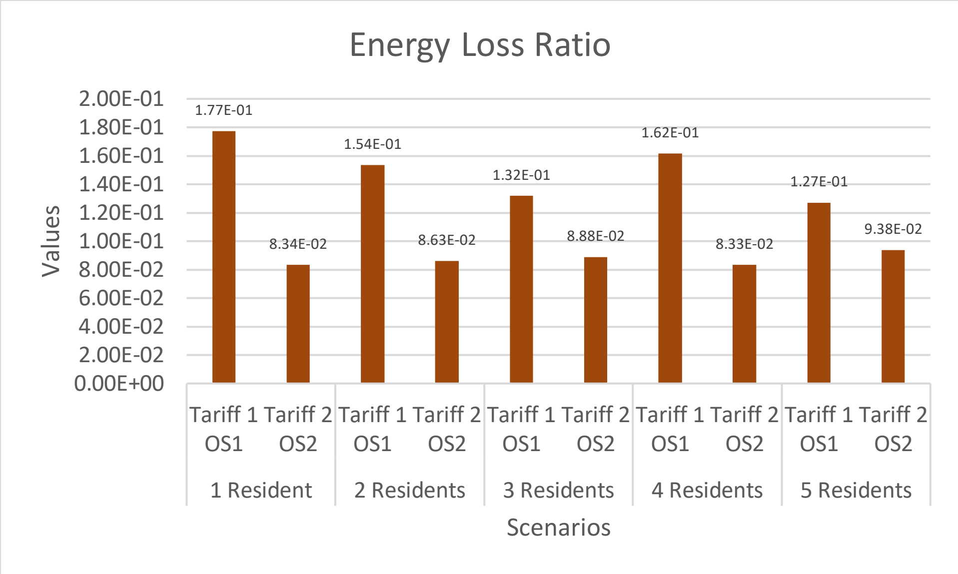

Figure 48 – Comparing Energy Loss Ratio for two types of Resident Behaviour (Type 1 and Type 2) across different types of residences

5.4.3 Scenarios of Model-Features

5.4.3.1 *Battery Degradation*

The simulation of battery degradation has been discussed in section 5.3.5.3, but it was not clear whether it would lead to significant impact on the Performance Indicators. In this section, simulations were run comparing system Performance Indicators with the steepest battery degradation slope (-0.00375) from Table 18, to system Performance Indicators where there is no degradation. The slope of the degradation affects the maximum capacity of the battery. The Performance Indicators were calculated for three types of residences, and the difference was calculated as a percentage of the simulation without battery degradation. Figure 49 shows that the magnitude of the difference is mostly under 1%, which may not be significant. However, since all the differences are in the same direction (all positive or negative) for each Performance Indicator, then the impact appears not to be random. Therefore, the impact could become more significant as the magnitude of the degradation slope increases.

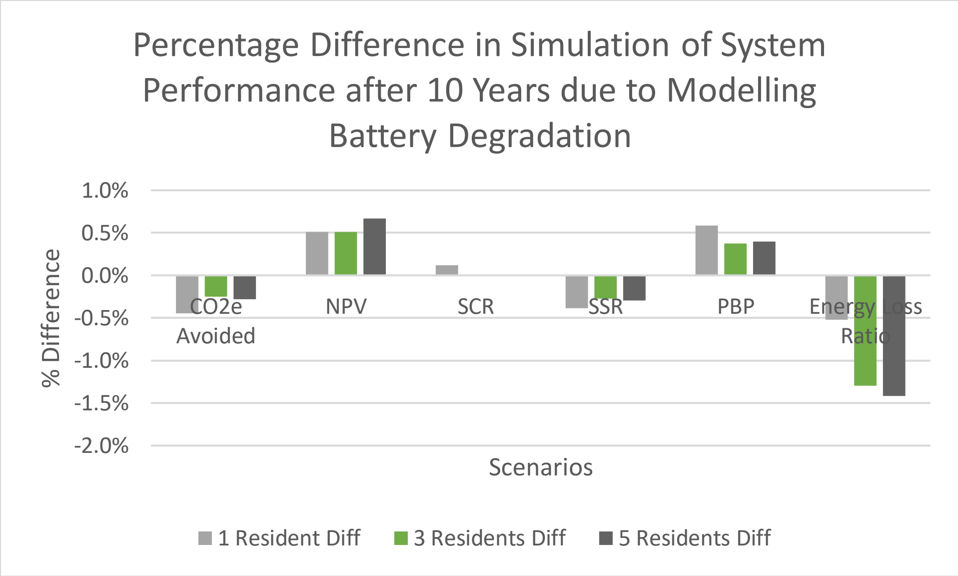

Figure 49 – Impact of modelling battery degradation on simulation results

5.4.3.2 *Non-Linear Conversion Efficiency*

The simulation of non-linear efficiency in inverters has been discussed in section 5.3.5.3. In this section, simulations were run comparing system Performance Indicators with non-linear efficiency to the system Performance Indicators where there is a constant efficiency of 90% for all inverter conversions. The system Performance Indicators was calculated for 3 types of residents based on number of residents, and the difference is calculated as a percentage of the simulation with a constant conversion efficiency. Taking Energy Loss Ratio as an example since it measures efficiency indirectly via energy loss, a negative difference indicates that the non-linear efficiency curve is more efficient; the ratio of most of the energy converted to the rated power of the inverter is more than what is required to reach the 90% efficiency on the non-linear curve. Figure 50 shows that the magnitude of the difference can reach 27%, which is more than a quarter. Also, the differences are in the same direction (positive or negative) for CO_2e Avoided, Energy Loss Ratio and SCR but not for NPV, PBP and SSR.

Those indicators with differences in different directions consistently differ only in the scenario with 1 resident, which could be ignored as an anomaly, but may require further investigation to ascertain if the difference falls in different directions. As to those indicators with difference in the same direction, the result can be explained. Since Energy Loss Ratio is consistently negative in Figure 50, less energy is lost with a non-linear efficiency. As to CO_2e Avoided, this is inversely proportional to Energy Loss Ratio because more energy is used or exported when Energy Loss Ratio is less, and more CO_2e is avoided when self-consumption increases. With SCR being consistently negative, it indicates that non-linear conversion leads to more energy loss and consequently self-consumption because less of the generated PV (in DC) gets to be used (as AC) to serve the Load Demand.

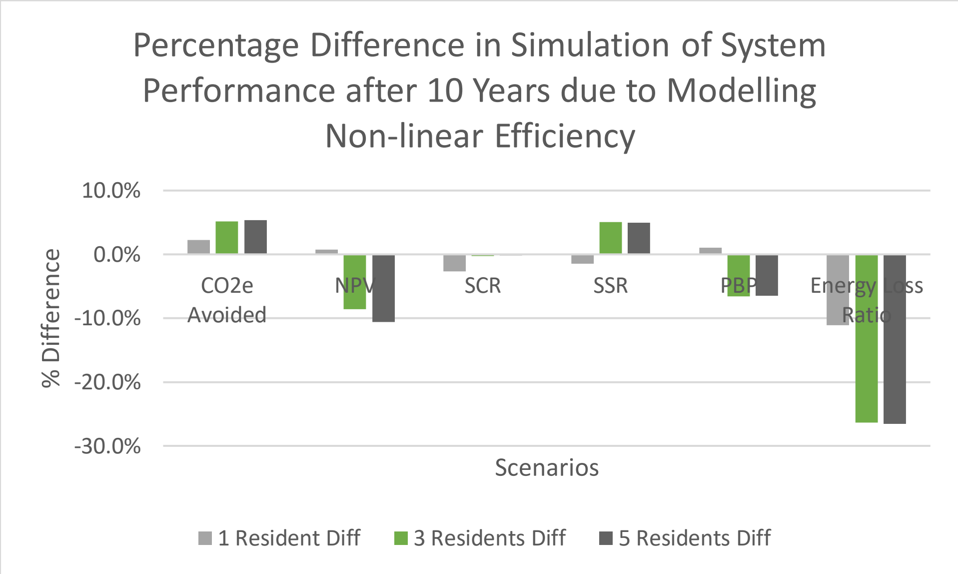

Figure 50 – Impact of modelling non-linear conversion efficiency on simulation results

5.4.4 Summary of Findings and Other Considerations

Prior to addressing the specific aims of this case-study, the context was set by exploring the trends in a base scenario. Furthermore, it was found that the small but negative discount rate (-0.25% in the UK at the time of study) may have led to exponential growth in NPV over 10 years. This property is present in all other scenarios because the same discount rate was used. Thereafter, the specific aims of the case-study were addressed.

First, the two aims on real-world decision-making compared operation strategies and also compared customer-types. While comparing operation strategies, OS2 outperforms OS1 economically, environmentally and technically in terms of Energy Loss Ratio, but OS1 performed better technically in terms of SCR and SSR. If each indicator holds equal weight, then OS2 is more sustainable, which means it is more sustainable to charge batteries to full charge at night when using ToU tariff; given the specifics of the model. Simple strategies like charging at night can yield better sustainability. On the other hand, while comparing customer-type, the ‘regular’ consumer outperformed the ‘smart’ consumer economically and technically in terms of SCR and SSR, but the smart consumers performed better environmentally and technically in terms of Energy Loss Ratio. Whilst counter intuitive, this finding cannot be generalised because of the specificity of the model-parameters and could be further explored.

Next, the two aims on modelling methodology were explored. Modelling battery degradation led to a difference of mostly less than 1% magnitude in the Performance Indicators after 10 years, and that may not be considered significant. However, the difference may become more significant, or less, as the number of residents increase, or rate of battery degradation increases. On the other hand, modelling non-linear (instead of constant) efficiency led to more significant differences in Performance Indicators over 10 years. Therefore, non-linear efficiency is highly recommended to be modelled in bottom-up models.

Given the assumptions of the simulation model, there are two considerations. The first is that increasingly, there are tariff options offered by residential electricity suppliers which are '100% green'. This is not necessarily achieved by sourcing the energy consumed from green sources directly but also indirectly, for example by matching 100% of a residence's electricity use with Guarantees of Origin certificates (GoO) or Renewable Energy Guarantee of Origins certificates (REGO). This study incorporated the fraction of fuel with emission used for electricity generation which is 37% based on UK data from the Department for Business Energy and Industrial Strategy. In the case where the grid offers 100% green energy, then the environmental effect of renewable sources at residences become redundant or minimised. Economically, the benefits of RES depends on the difference in electricity cost from the grid over time, and the cost of installing a PV system and batteries which are beneficial for price arbitrage. In the absence of residential PV and battery system, technical performance will be zero because self-consumption and self-sufficiency will fall to zero. Another consideration, especially in the UK, is that since the end of the new FiT registration was in March 2019, the only source of revenue used in the simulation model is from selling to the grid and avoided costs. Selling to the grid is encouraged by the Smart Export Guarantee (SEG) that came into effect on 1st January 2020.

With climate being a major determinant of the behaviour of systems with renewable energy sources, the effect of climate is implicit in the PV generation via two ways. The first way is in terms of the real PV generation data used in Chapter 4 which reflects the amount of sunshine (and cloud cover) during the period of data collection. The second way is in terms of input parameters for PV generation to the CREST model which was used in this chapter like hour angle, declination, solar altitude angle, azimuth of sun, and solar incident angle on panel; the panel parameters were obtained from project SENSIBLE's plan documents and manufacturer's specification sheets.

5.5 Conclusion

This chapter addressed the fourth thesis objective, which is to demonstrate an application of the SD model from Chapter 4 in decision-making. Using the SA framework from Chapter 3, the case-study in this chapter was designed to evaluate the performance of a RES in three dimensions of sustainability: technical, economic and environmental. The four aims of the designed case-study were divided into: two on real-world decision-making; and the other two on modelling features. Subsequently, four sets of scenarios were considered and analysed. The findings were summarised in Section 5.4.4.

Given the limitation of the modelling software to model up to 2 years at 1-minute resolution, options were considered for estimating the performance of a system in 10 years, using output from a 1-year simulation model. In Chapter 8, the SD model will be integrated with other RES to form an ICES, and similar analyses will be carried out. Furthermore, the supply-side model will be integrated with a demand-side SD model, also in Chapter 8. A demand-side SD model will be discussed in the next chapter.

6 Demand-side SD Models from the Bottom-up

6.1 Introduction

So far, supply-side SD models have been created in Chapter 4, and the model has been used for decision-making analysis in Chapter 5. The aim of this chapter is to create a valid demand-side SD model of RES from the bottom-up, which is the fifth thesis objective. The chapter begins by providing background to behaviour and activities in residential energy use, followed by a deeper look at how residential activities are measured, and existing demand-side models are reviewed. Then the model is conceptualised and formulated based on the modelling process from Chapter 3. Following the methodology section, results are discussed in terms of validation, other model outputs, complexity and evaluation of the model's aims. Finally, some conclusions are drawn and discussed.

A high-resolution simulation model that generates residential appliance load, which is the SD demand-side model, is presented. In addition to being realistic, the model aims to minimise historic coupling. Whilst the intermediary outputs of the modelling process are subjected to validity tests, the final output is validated by comparing statistical characteristics of the model's output to a validated model and data from real residences. The model shows potential to simplify the modelling process and to reduce the cost of modelling by driving the model on average frequency of appliance use instead of probability distributions of human activities. Other potential benefits include improved interpretability of the model and potential for participatory research. Other outputs from the model include distribution of appliances' activation and operation.

6.2 Literature Review

6.2.1 Energy Use, Behaviour and Activities

There is agreement that occupant behaviour is a major determinant of residential energy consumption [282]–[286]. In addition to recognising that occupants are the primary consumers of energy, not buildings [285], occupant behaviour can undermine technological solutions to efficient energy use [283], [284]. Behaviour is also recognised as a leverage point in public policy to influence energy use [282], [285], [286]. Another approach is to focus on energy consuming activities in households as policy levers, as in [12], [287], [288].

Whereas behaviour encapsulates actions, patterns of actions or manners of action, activities (or actions) may be a simpler construct to focus on especially for the purpose of simulating residential load. Everyday activities, in this context, refer to energy consuming activities in residential spaces, which may or may not involve an appliance; e.g. using a kettle or opening windows. There are a variety of theories explaining why individuals participate in everyday activities. In terms of relevance to this study, there are two groups categorised by their disciplines of origin as reviewed in [289]: psychology and time geography.

The psychological theories use concepts that are difficult to measure (or even define) for the purpose of simulation. Concepts – and consequently variables – required to understand behaviour have several definitions across studies which makes it difficult to generalise their findings; e.g. beliefs, values, attitudes and motives [284]. Other challenges include inconsistent and incomplete findings and a lack of a conceptual framework accepted by the majority of researchers [284]. In addition to the complexity that arises from the many and various determinants of human activities [289], their interaction is likely to further complicate it. For example, [290] has shown how multiple psychological subsystems interconnect when participating in an activity. "In psychology, as in the other life sciences, probably the best one can hope for is qualitative laws" [289].

The psychological theories explored are limited to decisions about single activities. For the purpose of simulation of residential energy use, the interest is in scheduling multiple activities. The next section explores theories from time geography, which seek spatiotemporal patterns of activities [289].

6.2.2 Properties of Activities

Even if we do not know why or how an activity gets to take place, knowing the properties of the activities could facilitate modelling the activities. Three properties of activities have been identified from the literature: activities are routinised but adaptable; activities are periodic; activities have meanings.

6.2.2.1 *Activities are routinised but adaptable*

Routinised is the property of being performed in a sequence. Some activities are bundled into a sequence for two reasons: constraints or availability of participants and resources [287]; or in anticipation of a prior or more important commitment [12]. Routines establish normalcy, hence the high reliance on routines to carry out activities [12]. It has also been found that routines get disrupted, but then normalcy returns [12], [287].

6.2.2.2 *Activities are periodic*

Implied in routine activities is that they are periodic. This is also supported by Time Use Surveys (TUS) which ask respondents about the frequency of their activities [268], [291]. Whilst periodicity may not be strictly mechanical and precise, it is a useful way to conceptualise activities that are repeated.

6.2.2.3 *Activities have meanings*

The meaning of an activity, or bundle of activities, has been found to be more important than management of energy use [12]. For example, to fulfil the meanings of "family comfort" or "quality family time", families do not mind if this is achieved by increased and expensive energy consumption [12]. Activities have meanings but the same meaning could be associated with different activities for different people, or in different residences or cultures. So while it is important to recognise that an activity may fulfil meanings, the activities – not their meanings – are more concretely associated with energy consumption.

6.2.3 Time Use Data

Time Use Data (TUD) provides information about how activities are located temporally and spatially with respect to other activities [292]. TUD is commonly collected via time diaries or Time Use Surveys (TUS), but other measurement techniques include Experience Sampling Method, Recall Self-reporting, Activity Checklist and computer-aided telephone interviewing [292].

Most TUS cover either a 24-hour period, or two 24 hour periods of a weekday and a weekend, per person. In a 2010 discussion paper on valid inferences that can be drawn from TUD [293], only one international TUD covering a seven day period could be identified. This limitation of available TUD has implications on what it can justifiably be used for.

It has been observed that certain properties of TUD make it a poor indicator of any long-run time use of an individual [293]; the properties are the short reference period (in Person-Day), and the large amount in day-to-day variation in time use (since people have different routines). Consequently, TUD is not suitable for policy related questions which require long run time use data [293].

Furthermore, it has been concluded that one person per household provides the same information as multiple persons per household, in a single day of TUD [293]. This is because of the "problem of disentangling the day-to-day covariance of activities from the long-run covariance" [293]. Another conclusion from the same study is that given the designs of multiple day TUS, much cannot be learned about intra-personal variability. The first conclusion may be due to a limitation of information captured by TUD. Moreover, building bottom-up energy demand models from TUD alone has been shown to be problematic because it is difficult attributing energy consumption to an activity, a specific time or even occupant [294].

The case-study is interested in the properties of activities that could be used to model a simulation of residential load, intra-personal variability and also activities' interrelationship which has been acknowledged in [12], [287], [288]. For these, data covering more than a day or two would be required.

Whilst some studies have proposed methods that could be used to identify influence among activities in TUD using network theory [295] and co-variance analysis [296], these analyses would still lead to inferences about a population, not a person or household. This is similarly the case when TUD is used to extract probability distributions of activities in simulating residential load.

6.2.4 Models of Bottom-Up Residential Load

6.2.4.1 *The State of The Art*

There are many models that predict the interaction of occupants with buildings, which has impact on energy consumption of the buildings; examples include windows [297]–[301], blinds [302], [303], lighting [304] and air condition [305]. Such predictive models – in addition to occupancy and movement in buildings – can be integrated to Building Performance Simulation software using the obXML schema which is based on the DNAS (Drivers, Needs, Action, System) framework [306], [307]. Taking it further, [308] presents a "platform" comprising models of interaction with building, agent-based models of synthetic occupants, stochastic models of activities and interfaces to integrate with building energy simulation models (e.g. EnergyPlus). However, residential load is not the focus and was not discussed.

A bottom-up simulation model of residential load outputs electricity load of a household based on more elementary load components, which could be a household when dealing with multiple households, or appliances when dealing with a single household [309]. Bottom-up models have been categorised based on scale [309] and include electricity demand models and end-use models. Electricity demand models output load at utility level, which is multiple residences, while end-use models output load at residential level. These two require different input data, and whilst electricity demand models can be estimated using an accounting method that estimates aggregate residential electricity consumption, it is less the case with end-use models which require simulation to capture the dynamics within a residence. Also, end-use models can be used to build electricity demand models, as demonstrated in [309]–[311].

Therefore, a bottom-up model at residential level could be broken down into three aspects: the set of appliances in the household, the individual electricity demand of these appliances and the use of the appliances [310]. The first two can be considered the static aspects, while the last is the driver of the model's dynamics because it determines the state of the system in progressive time-steps.

Table 23 shows some bottom-up models of residential load highlighting the main model outputs, inputs, drivers and aims. Statistical realism refers to output of the simulation having statistical properties of the real system. A model outcome that is statistically realistic could be used as input to other simulation models in place of field data; e.g. Demand Side Management, building simulation and low voltage grid simulation [310].

Reference	**Outputs**	**Inputs**	**Drivers**	**Aims**
[312]	Load of the average residence; conservation effects; weather sensitivity	Appliance stock or saturation; sociodemographic characteristics.	Accounting methods	Forecast; what-if analysis.
[313]	Load of residences and community; hot water energy consumption (daily);	Occupancy patterns; energy consumption of appliances (daily);	Accounting methods	Forecast; energy system design.

[304]	Lighting	TUD (occupants' activities);	Stochastic modelling	Statistical realism
[309]	Load of residence	Appliance ownership; daily usage pattern of appliances.	Probability distribution	Statistical realism
[311]	Load of residence	TUD (occupants' activities and occupancy); appliance energy consumption.	Probability distribution	Statistical realism
[314]	Load of residence; hot water demand	TUD; mean appliance energy consumption; water tap data; daylight data.	Appliance (operation) power conversion scheme;	Statistical realism
[310]	Load of residence; synthetic activity sequence	TUD (occupants' activities); appliance energy consumption; appliance stock or saturation.	Markov chain (non-homogenous)	Statistical realism
[315]	Load of residence and community	Appliance energy consumption;	Psychological model of human desire	Statistical realism

Table 23 – Models of energy use at different scales

The models in Table 23 take different approaches. The load of an average residence is estimated which is serviced by a single utility company based on appliance stock and sociodemographic characteristics [312]. Whereas [312] considers itself an end-use model, it is actually an electricity demand model according to the distinction in [309]. Similarly, [313] is a load estimation model for residential and communal load called SMLP (Simple Method for formulating Load Profile) based on occupancy and energy consumption of appliances. On the other hand, [309] provides an end-use model based on appliance ownership and appliance usage expressed as probability distributions on different time scales. Similarly, [311] employs probability distribution based on occupants' activities and active occupancy and energy consumption of appliances to create a realistic residential load. Taking a different approach, [310] focuses on first generating synthetic activity sequences, then using data on energy consumption of appliances and energy-use pattern of the appliances to generate residential load. Finally, [315] relies on the model of human desire from Psychology, in addition to other parameters, to generate realistic residential load.

6.2.4.2 *Limitations*

Most of the models in Table 23 aiming for statistical realism rely on TUD to drive the models. Some of the limitations of TUD have been explored in Section 6.2.3. TUD captures occupant activities in time, which is then incorporated into the simulation models as a form of probability distribution. Since the probability distributions are historic correlations, the models are tightly fitted to the source field data (TUD) especially given the typical high resolution of 10 minutes. To apply the models to different situations which may have different structural properties and consequently different correlations, the probability distribution would need to be updated, which may lead to new TUS which is resource intensive. To minimise the impact of this limitation, this study aims to model occupant activities based on simpler properties of activities which may not be as tightly coupled to historic correlation. It is therefore expected that the probability distribution of activities can emerge as by-products from the simulation, rather than as an input. It may be less accurate, but it is fit for use.

The second limitation is to do with the approach to validation of the models aiming for statistical realism. The models assume that if the output of the simulation model is realistic, then the conceptual model is either realistic or inconsequential. The limitation is that no attention is given to validating the conceptual model and other intermediary steps. Whilst the models probably undergo several iterations before the final output, a framework to validate the modelling process is not made explicit.

6.3 Methodology

The modelling process follows the flow presented in Chapter 3 (Section 3.2.1). There are three modelling stages in the following order where output from an earlier stage serves as input to the latter stage: Problem Articulation; Model Conception; Model Formulation. The outputs from the stages are Model Boundary Chart, conceptual model and the final output is a valid simulation model. Meanwhile, at each stage, validity tests are carried out such that when the output of a stage fails a validity test, the stage is revisited and adjusted. The three stages will be discussed in subsequent sections.

6.3.1 Problem Articulation

6.3.1.1 *Problem Definition*

The purpose of the model is to generate a residential load that aims to be realistic and minimise historic coupling via a bottom-up approach. Being realistic refers to statistical plausibility when compared to measured data from a real system or a simulation model validated with measured data; which makes it more representative of real systems. Minimising the historic coupling of a model refers to minimising over-fitting between what drives the model and historic correlations like probabilities derived from real residences; which should make the model applicable to wider scenarios.

6.3.1.2 *Model Boundary Chart*

Table 24 shows the endogenous and exogenous variables in the system in the Model Boundary Chart (MBC), with their units in parenthesis. The boundary of the model is defined by the endogenous and exogenous variables; the endogenous variables depend on the exogenous. The boundary adequacy of the model is assessed based on whether the variables support the purpose of the model. Alternatively, it may be asked: is there a variable in Table 24 that should not be present in the model, or is there a variable that should be present but is not? Unlike systems where the conceptual model is generally understood, it may not be possible to address these questions well without understanding how they interact. In other words, the conceptual model needs to be understood before fully addressing these questions. Therefore, if the conceptual model is well argued to be valid, then the MBC of the conceptual model can be accepted as well.

Endogenous Variables	**Exogenous Variables**
Activity timer (minutes) Occupant’s attention (dimensionless)	Appliance/Activity cycle per time (1/minutes) Number of residents (dimensionless)

Appliance activation (dimensionless) State of appliance's operation (dimensionless) Power consumption of appliances (kW) Total power consumption of residence (kW)	Occupancy of residents (dimensionless) Mean duration of appliance operation (minutes) Mean energy consumption of appliances (kW-minutes)

Table 24 – Model Boundary Chart of the model showing the main variables

6.3.2 Model Conception

This section looks into the conceptual model and addresses the concerns of validity tests raised in Chapter 3 (Section 3.2.2). A conceptual model presents the structure of a system. The conceptual model can be understood from four perspectives: aggregation; relationships; constraints and assumptions on the behaviour of residents. These perspectives were informed by Structure Verification validity tests (see Table 5). The conceptual model is presented as a CLD (Figure 51 to Figure 55), and it is the outcome of developing and testing multiple concepts based on the literature and progressive iterations.

Aggregation: At the level of a residence, the main causes of power consumption are appliances, and most appliances operate based on the activities of the residents. Residents are defined by their activities which are influenced by the occupancy and attention of the residents. Activities are conceptualised as timers, appliances as power load, while occupancy and attention as on and off switches but occupancy is exogenous whereas attention is endogenous. Activities have been described as timers because activities have been shown to be periodic and have patterns in [12], [287]. Currently, activities are described as tied to only one appliance; e.g. there is no activity 'cooking' which may involve multiple devices, but instead there is an activity 'use kettle' and another 'use microwave'. Therefore, a conceptual model which describes activities, occupancy, attention and appliances offers an appropriate level of aggregation for modelling residential load demand. Figure 51 shows a CLD of the components at the chosen level of aggregation from the perspective of a single resident. The two types of appliances (Appliance A and Appliance B) relate to the resident's attention differently.

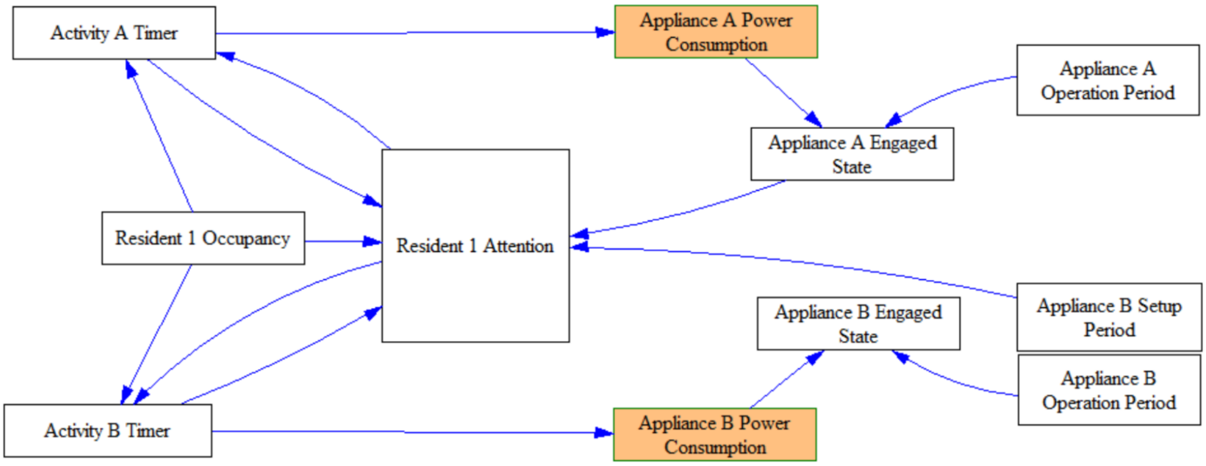

Figure 51 – CLD showing interacting components of a single resident with two types of activities and appliances

Relationships: In the absence of automated scheduling of appliances, a resident commits their attention when carrying out activities, and the attention is influenced differently by type of appliance (see Figure 51); either depending on the appliance's engaged state or set up period. Also, at any time, a resident can either be at the residence or not; and activities in the residence require active occupancy of the resident. Each resident can carry out multiple activities and each power consuming activity requires the operation of one appliance. However, automatic appliances like fridges operate without prompt from a resident and are modelled as periodic power consumption that is ever-present. The standby power consumption of appliances is also modelled (see Figure 52). Therefore, the relationships among elements in the system is based on valid observations and the literature.

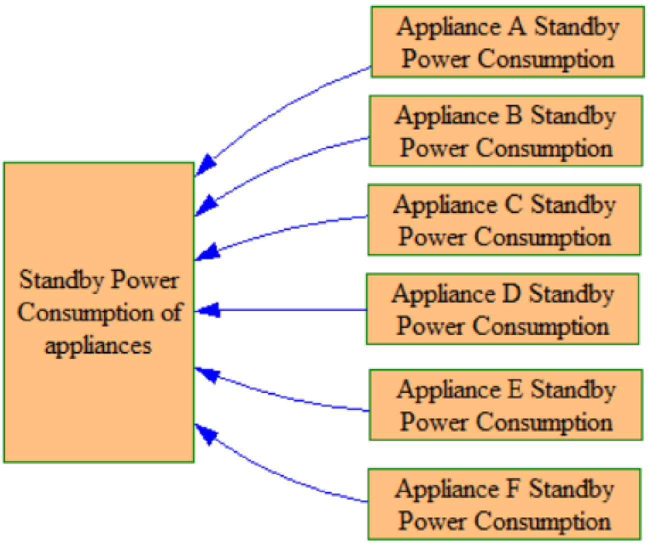

Figure 52 – CLD showing standby power consumption of appliances

Constraints: Attention of residents is finite but residents multitask, as acknowledged in TUS design which distinguishes simultaneous activities as primary and secondary activities, as found in [268], [291]. Whilst not all activities are power consuming, residents have also been shown to perform multiple power consuming activities simultaneously [288]. However, a limit to the number of power consuming activities a resident can be engaged in simultaneously shall be limited and reasonable. Some power consuming activities are semi-automatic (e.g. using a washing machine) which requires the resident's attention to setup but not for the duration of the operation of the appliance, as acknowledged in [310], [314]; for example, the resident's attention in Figure 51 is determined by the setup period of Appliance B which may be shorter than the engaged state. Another constraint is the state of a resident's occupancy determines whether an activity is initiated or not; the resident must be at the residence for an activity to occur, especially the part of the activity that requires the attention of the resident. Finally, appliances in a residence are finite, which means the availability of an appliance is a constraint in a residence with multiple residents who may be ready to use a single appliance while it is engaged by another resident.

Assumptions on the behaviour of residents: It has been assumed that residents are able to estimate whether the end of an activity that requires their attention will be outside the time they are scheduled to be in the residence, and consequently, they will refuse to engage in an activity even for the duration of the available time. Also, residents do not share the same appliance concurrently (Figure 53). Lighting has been modelled based on the assumption that when an appliance is in use, the set of lights in the room is turned on; and lights are turned off when no appliance is in use in a room (see Figure 54). This is the case regardless of the time of day and it should not make a significant difference because LED bulbs are assumed given their ubiquity and low power consumption.

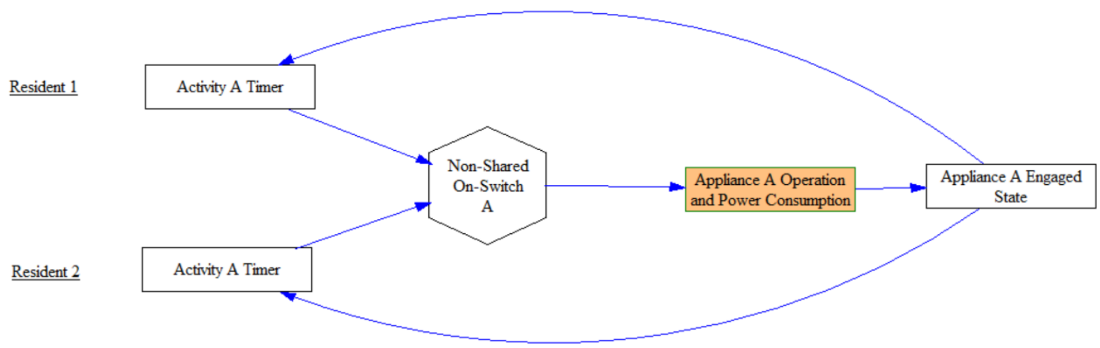

Figure 53 – CLD showing that appliances are not shared concurrently

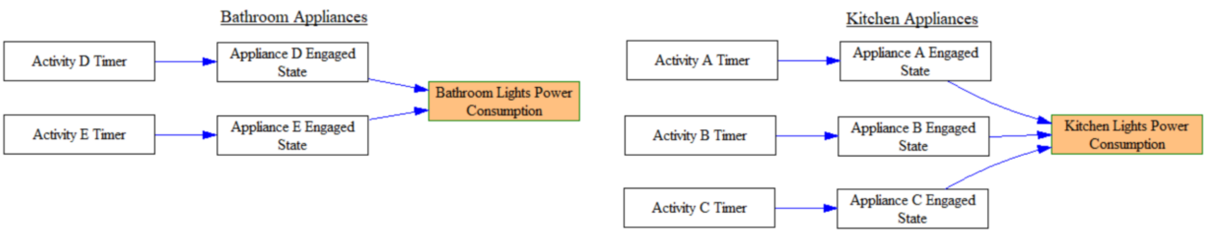

Figure 54 – CLD showing residential lighting

The residential load is an aggregation of all the power consumption of the appliances shown in the diagrams of the conceptual model with orange fill; shown in Figure 55.

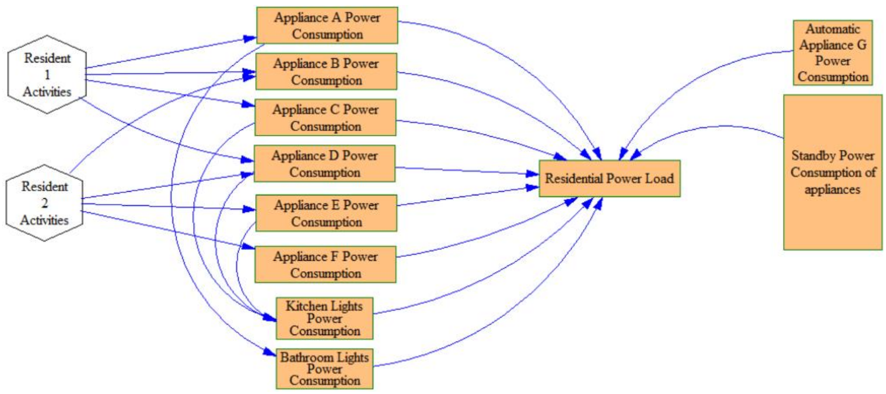

Figure 55 – CLD showing residential power load

6.3.3 Model Formulation

This section presents the simulation model (Section 6.3.3.1) developed from the conceptual model, while addressing the concerns of validity tests raised in Table 5. The logic and formulation of the simulation model is explored along with the behaviour outcome (Section 6.3.3.2). Then the source of values for calibrating parameters are presented (Section 6.3.3.3), as well as introducing behaviour reproduction (Section 6.3.3.5).

6.3.3.1 *Simulation Model*

Activity has been implemented as a countdown timer in SFD; see Figure 56. As a timer, the following properties of activities are captured (see Section 6.2.2): periodic and routinised but adaptable. The timer corrects for delays which is tracked by the Due-Time Correction Factor. An activity being due is not sufficient to activate the associated appliance but depends on other variables, as well as resolution of conflict when multiple activities are due at the same time since the available attention of the resident is limited. The necessary conditions for activation of appliances is further discussed in Section 6.3.3.2. The two types of appliances are shown in Figure 57 and Figure 58: a kettle is modelled as requiring the attention of the resident while on; whereas a washing machine is modelled as requiring the resident's attention only for a setup period, not the entire operating cycle. To model the efficiency improvement of an appliance, 'Power per User' can be decreased for more efficient appliances and increased for less efficient appliances. Figure 59 shows the limited attention of a resident being dependent on the occupancy of the resident, as well as the activation and deactivation of appliances.

The simulation was run for three types of residences with one, two and three residents for the duration of a year. Since additional residents lead to marginal increase in residential load [294], the maximum of three residents which is simulated could represent more residents in real residences.

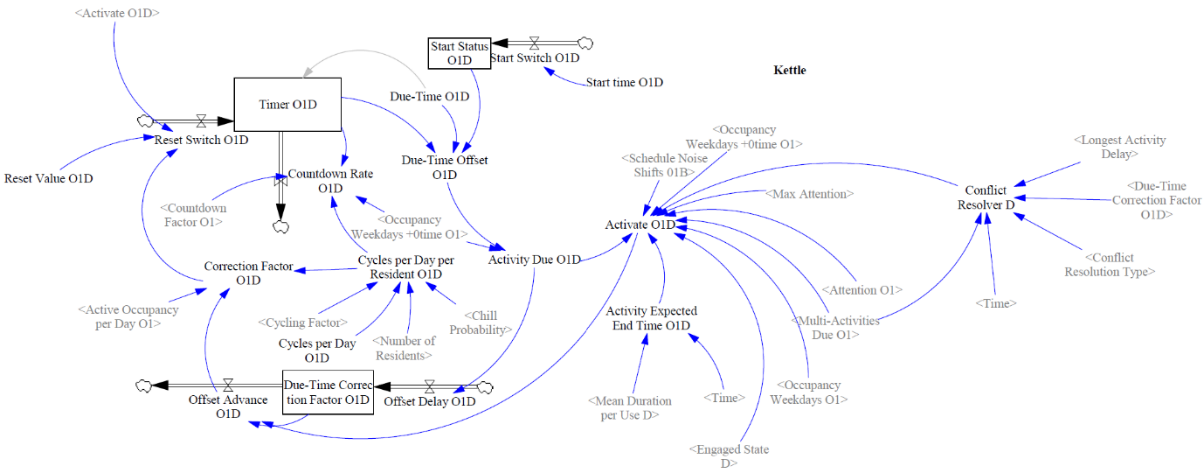

Figure 56 – SFD of an activity for Kettle use

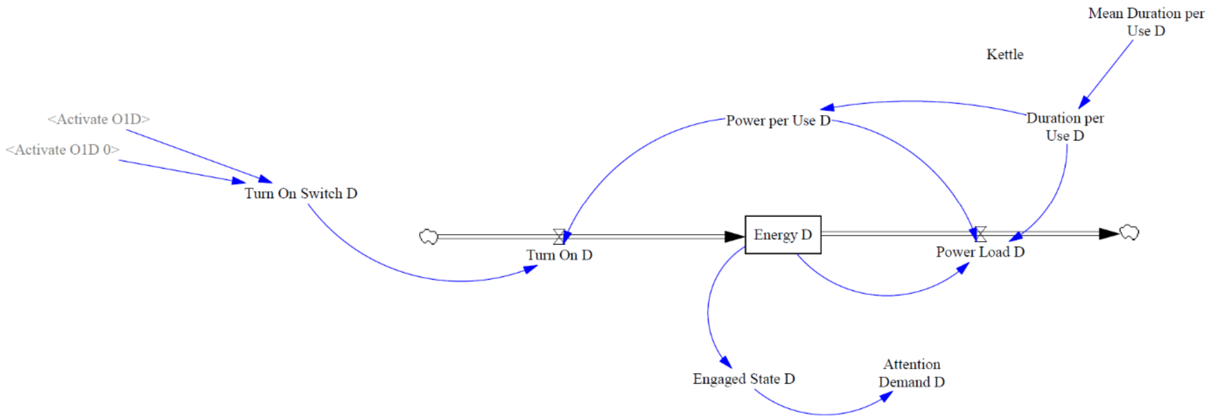

Figure 57 – SFD of an appliance that requires attention while turned on: Kettle

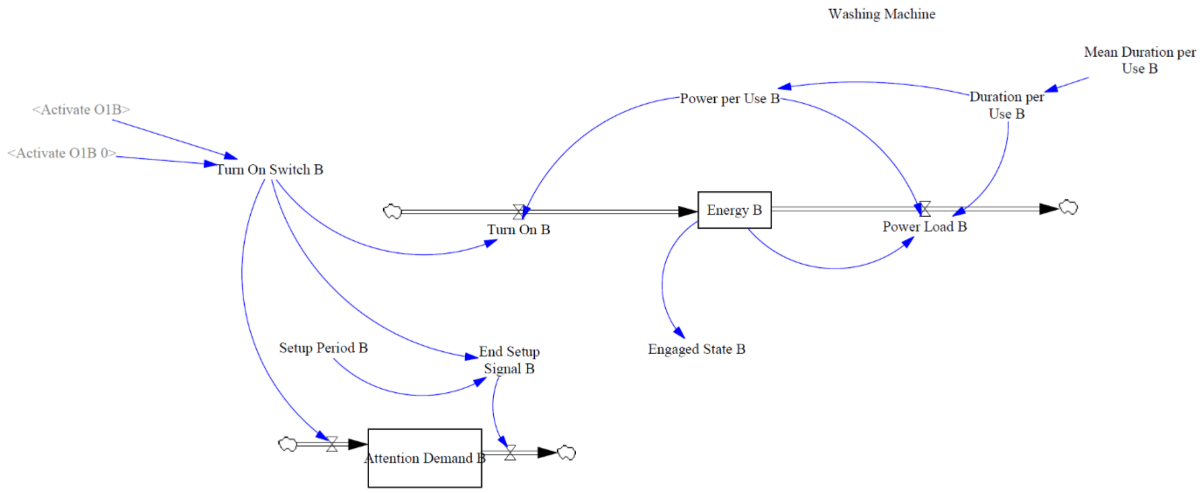

Figure 58 – SFD of an appliance that requires attention only during setup: Washing machine

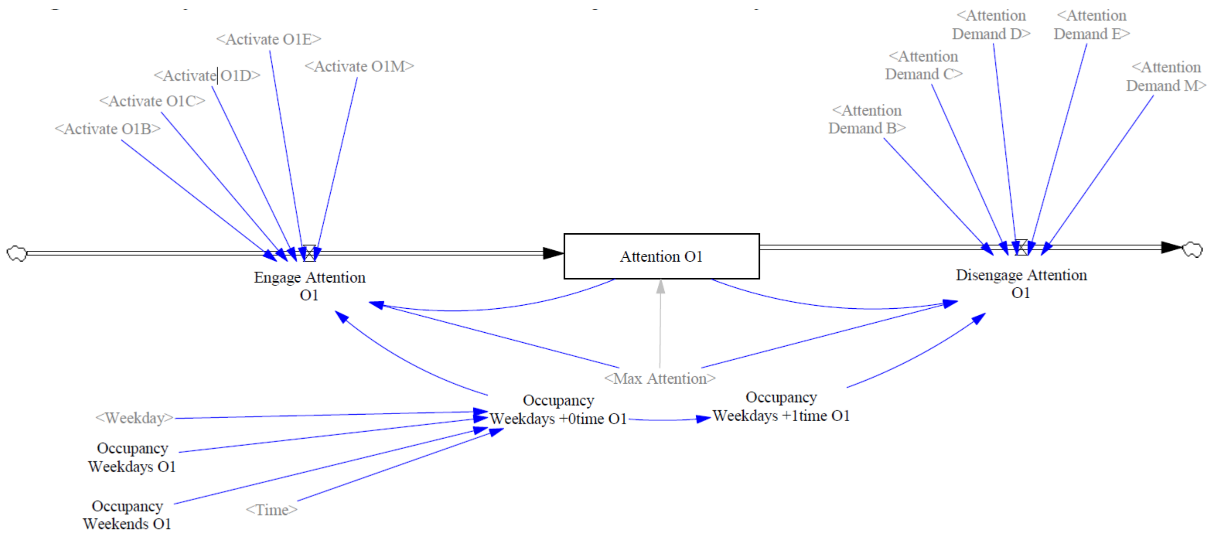

Figure 59 – SFD of attention of a resident

6.3.3.2 *Model Formulation*

The simulation model can be further elaborated by looking at the operational logic of the endogenous variables. Figure 60 shows a flowchart of the operational logic of an activity and its related appliance. When resetting the activity timer, the timer is adjusted for the counted delay before the delay counter is reset. There are multiple conditions required to activate an appliance and detailing them would make the flowchart cumbersome; also shown in Figure 56 as the variables pointing to Activate. The conditions to activate in the most basic set up of the model are: active occupancy at the start time of the activity; availability of attention of the resident; availability of the appliance; occupancy at the estimated end of activity and conflict resolved in favour of the activity in situations where multiple activities are due. Conflict resolution is implemented such that the longest activity due is carried out.

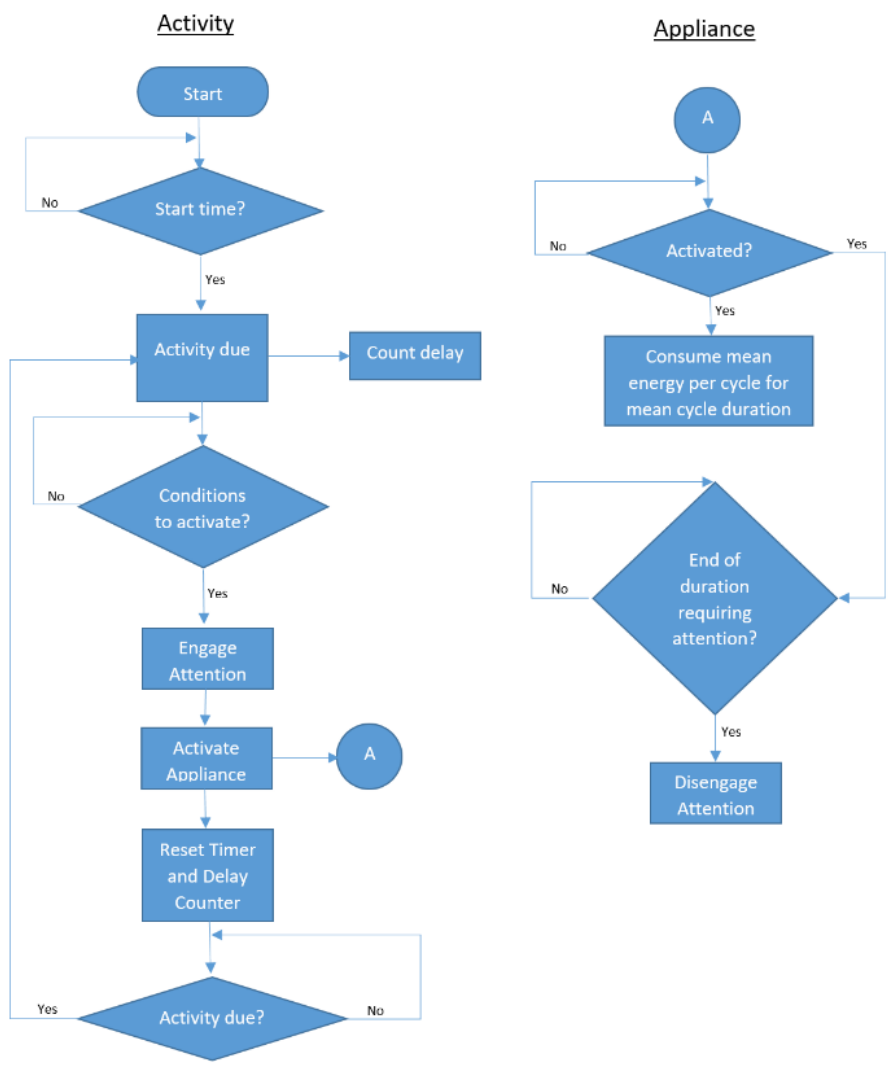

Figure 60 – Flowchart of the operational logic of activities and appliances

The activity timer is implemented as an exponential decay such that the countdown timer is never negative. The advantage of an exponential decay over a linear function is that there is less precision in the activity cycles which makes it perhaps more realistic to a human mental model of time tracking. The cycle duration for different active occupancy durations of a resident has been implemented as an exogenous non-linear variable.

Figure 61 illustrates some the behaviour of the timer in three different cycle conditions shown as six full cycles. A cycle is a ramp made of a vertical line and a downward curved slope up to the next vertical line. The first and last cycles are conditions with no constraint which shows a cycle of about 600 minutes. The second and fifth cycles show that the timer pauses during inactive occupancy (occupancy = 0). The third cycle shows a cycle that is delayed by about 200 minutes (because some conditions have not been met) and the delay is adjusted in the fourth cycle by the amplitude of the ramp. Furthermore, Figure 62 shows the behaviour of attention which depends on occupancy (see Figure 59) for the duration of 7 days; attention goes to the maximum available attention (which is set to 2) during inactive occupancy (occupancy = 0) so that no activity can be carried out in the residence, otherwise attention varies between 0 and the maximum, depending on activities that are due.

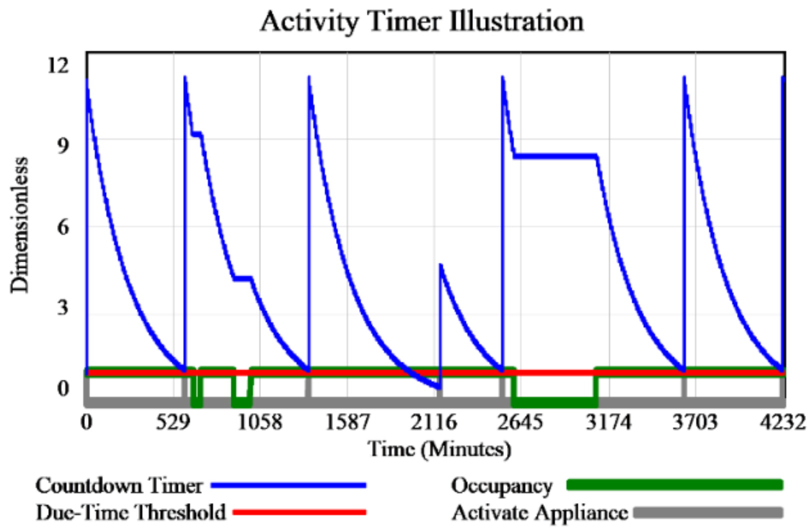

Figure 61 – Behaviour of Activity Timer in 3 conditions

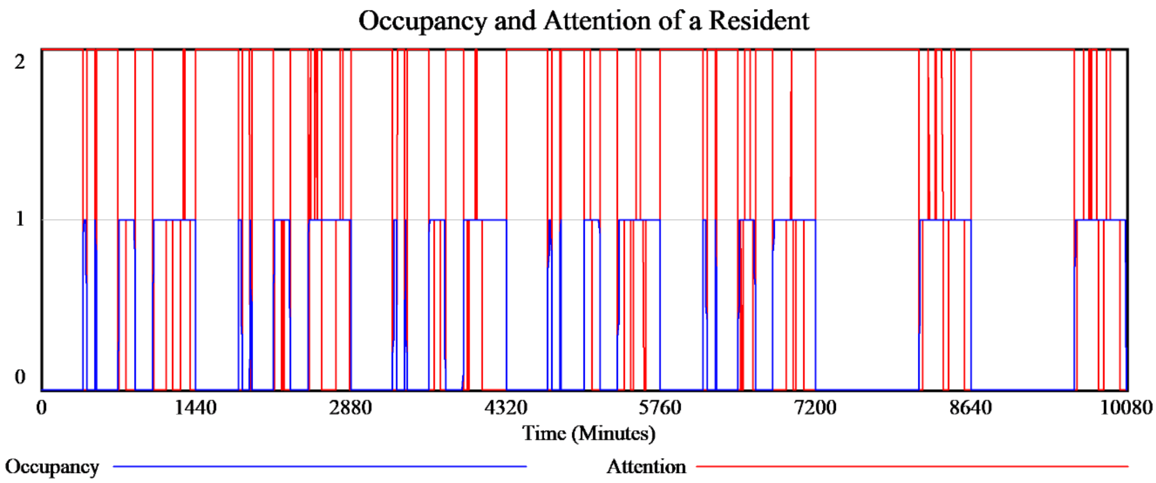

Figure 62 – Occupancy and Attention for 7 days

6.3.3.3 *Parameter Verification and Calibration*

Table 25 lists the system parameters and the source of values used to calibrate them; all parameters are exogenous variables. The values of most of the parameters are sourced from the CREST model; which has been well documented [316]; the choice of the CREST model is discussed in Section 6.3.3.5. In the case of activity frequency (Mean Base Cycles per Year), a scaling factor is included which is adjusted until the sum of residential load in the SD model is close to that of the CREST model; because activity frequency in the CREST model is an average from a population of non-homogenous residences, which is mediated/adjusted by probability distributions relevant to the residence type. However, the scaling factor is applied to all activities and therefore the proportion of frequencies/cycles among appliances is maintained. Figure 63 shows the annual mean and sum of the models as calibrated with scaling factors of 0.6, 0.75 and 1.2 for residences with one, two and three residents respectively. Figure 63 does not show the monthly trends because available data on appliances from the CREST model are annual averages, not monthly.

Parameter	**Source**
Mean energy consumption of appliances per cycle	Mean cycle power (CREST model) Standby power (CREST model)
Mean duration of appliances operation cycle	Mean cycle length (CREST model) Delay restart after cycle (CREST model)
Frequency of appliance use (Appliance cycle per time)	Mean base cycles per year (CREST model)
Start times of appliances/activities	Modeller's choice
Appliances available and quantity	Same as parameters set in CREST model being compared
Number of residents	Same as parameters set in CREST model being compared
Occupancy/schedule of residents	Same as parameters set in CREST model being compared
Maximum attention capacity	Modeller's choice; 2 is the default. This allows for multitasking as well as for residents to carry out other activities while their attention is waiting for the most due activity to be performed.

Table 25 – System parameters and sources of calibrated values

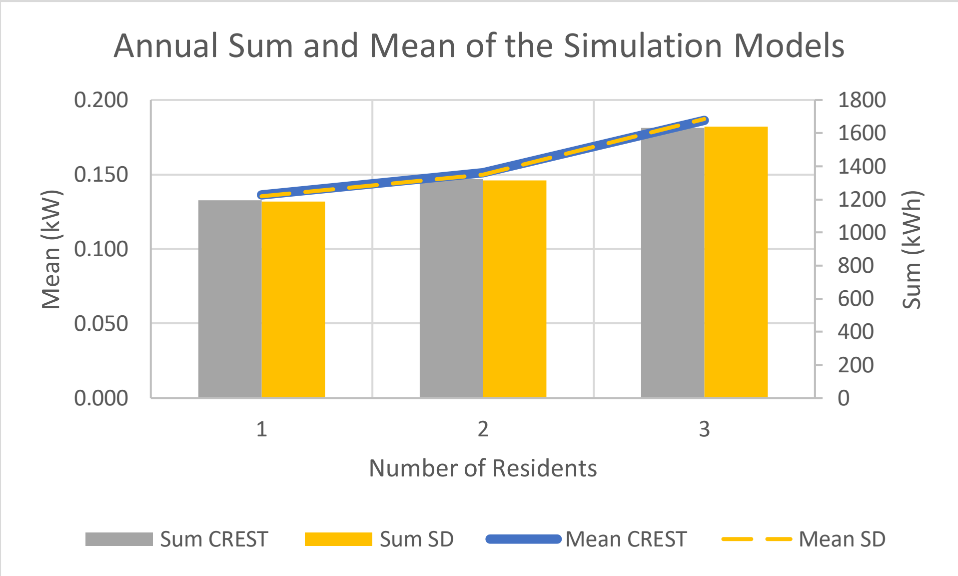

Figure 63 – Calibrated sum and mean of the SD models by adjusting the scaling factor of the activity frequency

There is a secondary group of parameters that add stochasticity to the model; termed the noise parameters. These achieve stochasticity by randomly modifying an associated parameter around its mean value. The noise parameters include: Schedule Shift Noise and Appliance Duration Shift Noise. Schedule Shift Noise moves occupancy forward or backward every 24 hours, while Appliance Duration Shift Noise changes the duration of the appliance's operation every cycle. All the noise parameters are based on the Normal Distribution with the mean set as the calibrated value of the associated parameter. The standard deviation for Schedule Shift Noise is set to 8 minutes, while for Appliance Duration Shift Noise, it is 30% percent of the magnitude. Being random noise, the accumulated effect is cancelled out at the end of the simulation of 525,000 minutes.

6.3.3.4 *Extreme Conditions*

Most of the extreme and unrealistic conditions that could arise in the model are controlled in the logic of the model; e.g. only one resident can use an appliance at the same time instead of multiple or infinite number. Other controls are specified as parameters e.g. maximum attention per resident set to 2.

6.3.3.5 *Behaviour Reproduction*

The aim of behaviour reproduction is to evaluate the similarities of the model's output to a reference dataset. The reference dataset could be a measured residential load or a synthetic residential load which has been validated against measured residential load. Table 26 shows behaviours that will be tested which are based on validations carried out in [310] and [311], but limited to statistical characteristics that apply to a single residence, while also excluding characteristics showing the effects of some limitations of the model (e.g. seasons). The simulation model is run at 1-minute time-steps for the duration of one year.

Property	**Description**
Load profile	Plot of the output load of the residence per minute
Annual mean daily load profile	Plot of the annual mean load for every minute of a day
Hourly load duration curve	Plot of the hourly mean load for a year in descending order

Table 26 – Statistical properties for comparison and brief description

High resolution measured data on residential load demand is available like the UK-DALE dataset [317] and the UKDA-6385 dataset [207], but comparing these quantitatively with the SD model's output is challenging because some of the calibrated parameters of the SD model that define scenarios are not specified in the datasets; e.g. active occupancy of residents, number of residents, power consumption of appliances and available appliances. In the UKDA dataset, there are data on available appliances and number of residents, whereas in the UK-DALE dataset, there are data on available appliances and their power consumption only.

On the other hand, the output dataset from the CREST model [316] could be used for validation because many of the model-parameters can be extracted from the input parameters of the CREST model. This has been shown in the parameter calibration Table 25. However, the CREST model has a limitation, which is that its output represents an average residence from a population because the model is driven by probability distributions generated from TUD, which covers many residences in two days (a weekday and a weekend). In contrast, the SD model in this study aims to simulate a single residence across many days. Hence a dataset from a single residence, or simulated based on data from a single residence, would be preferred, and therefore behaviour comparison is carried out in light of this limitation.

Based on the above, there are two aspects to behaviour comparison: a visual-quantitative and a qualitative aspect. Visual-quantitative comparison refers to visual comparison of plots on quantitative axes. The visual-quantitative comparison is between SD and CREST models on how well the former matches the latter on a two-dimensional surface of power consumption and time. A purely quantitative comparison is tedious and inconclusive for time series – without qualitative judgement – according to sources like [318]–[321]. Moreover, all the reviewed literature on synthetic residential load focus on visual comparison to validate at individual-residence level. On the other hand, the qualitative comparison first identifies some qualitative properties of real measurements (UKDA dataset), then compares the two models on how well they exhibit those properties.

Since the CREST model allows for the SD model to be calibrated better for comparison, a few adjustments have been made in the CREST model: maintain the same appliances and occupancy schedule for weekdays and another for weekends, for the simulation period of a year. The appliances selected and their quantity for the residence is provided in Table 27. The main measured residence to be compared with from the UKDA dataset (with 2 residents) has the same appliances as in Table 27, however the power consumption of the appliances are not available. The residents are assumed not to be children because every resident has access to all the appliances. Children may have access to none or few, which may not be operated by them in reality but would be determined by their routine.

Appliance	**Quantity**
Fridge freezer	1
Personal computer	1
TV	1
Microwave	1
Kettle	1
Washing machine	1

Table 27 – Appliances in each residence

As seen on Table 27, other common appliances, especially HVAC appliances, have not been included in the model. The rationale is that most domestic heating in the UK is on gas, which is a significant power load. 86% of houses in the UK use gas fuel for heating at the time of the case-study (2019) [322], remaining about the same at 87% in 2021 while only 7% use electricity [323]. Furthermore, HVAC is not required to validate a SD model that generates realistic residential load because the residences used to validate the model, both from the CREST model and UKDA dataset do not have HVAC on electricity. Should there be a need to include HVAC in the model, they can be modelled as electric loads with operation patterns similar to appliances that have already been modelled. For example: space heating and cooling could be a load that turns on periodically (due to its thermostat), like the fridge, but only during occupancy; alternatively, space heating and boiler-storage combination can be independent of occupancy and be programmed to turn on periodically during specific hours of the day (assuming a scheduled thermostat); electric shower could be modelled like a kettle which depends on occupancy. Required HVAC parameters like average annual frequency, cycle length and average power consumption per cycle length are available from [208] based on surveys. Unlike the modelled appliances, HVAC appliances could also be modelled to respond to the weather data.

6.4 Results and Discussion

6.4.1 Behaviour Comparison

6.4.1.1 *Load Profile*

The load profiles for a 7-day period for the CREST model, SD model and a residence from UKDA dataset are shown in Figure 64, Figure 65 and Figure 66 respectively; all have two residents. Figure 66 is the residence with the same appliances as the CREST and SD models. The three load profiles highlight the similarities of varying and steep peaks resulting from different activities, as well as similar amplitudes between the CREST and SD models. The absence of these similarities would terminate further comparisons.

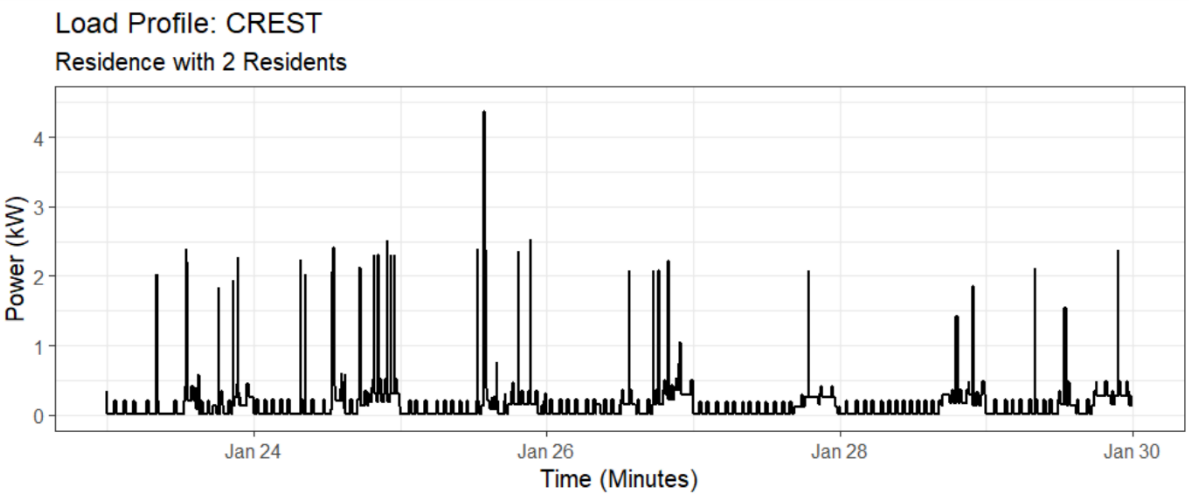

Figure 64 – Load Profile from CREST model

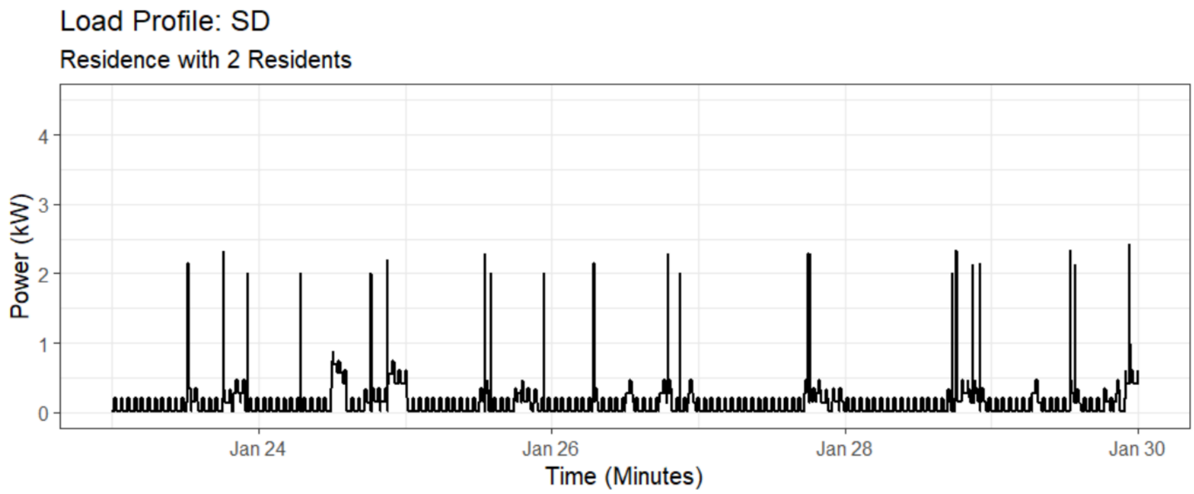

Figure 65 – Load Profile from SD model

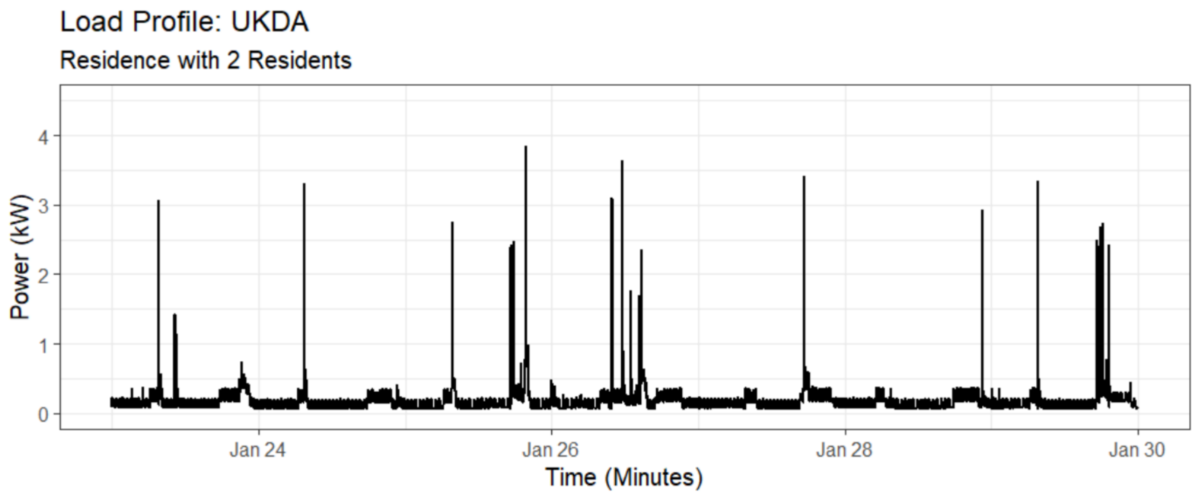

Figure 66 – Load Profile measured from a residence in the UKDA dataset

Looking at the period of a week in Figure 64 – Figure 66, there is significant difference in peak amplitude between SD and UKDA, but not between SD and CREST. The similarity in average amplitude between SD and CREST is because the parameters of appliances in SD were obtained from CREST. The doubling of peak amplitude in CREST is an outlier which can occur in SD at a different time. However, the difference in average peak between SD and UKDA is likely due to higher power consumption of appliances in the UKDA residence, which is not available in the UKDA data. Nonetheless, the three models (Figure 64 – Figure 66) show similar qualitative properties: intermittent peaks, short but consistent low power cycles and sparse intermediate power cycles lasting several minutes for the duration of appliance cycles (e.g. washing machine).

The aggregate energy for the period in Figure 64 – Figure 66 is 24.60 kWh, 27.85 kWh and 30.30 kWh for SD, CREST and UKDA respectively, which indicates that the appliances in

UKDA consume the most power and that the difference between SD and CREST would be smaller were it not for the outlier in CREST. However, these values represent a short period of a week, and it cannot be generalised for other parts of the year especially given the limitation that SD does not model seasonal variation in residential load. For a more comprehensive qualitative comparison, which should be between SD and CREST, the annual energy consumption for SD and CREST have been shown in Figure 63.

6.4.1.2 *Annual Mean Daily Load Profile (AMDLP)*

Residential load profiles are not suitable for comparing the models over a long period of time like a year at 1-minute resolution because the data points are many and the entire dataset is considered a single instance of the data; a year's data could be split into instances of sub-units like weeks or days. The AMDLP summarises a year's load profile by plotting the annual average of every minute in a day, and this addresses the limitations of load profiles. In this section, the AMDLP plots will be explained first, then a visual-quantitative and qualitative comparison, as explained in Section 6.3.3.5.

Figure 67 and Figure 68 compare the AMDLP of the SD model with the corresponding CREST model having similar parameters for residences with two and three residences respectively. The plots show clusters of peaks which coincides with the active occupancy for weekdays and weekends; the weighted weekly occupancy of the two residence types are provided in Figure 69.

Figure 70 shows the AMDLP of measured residences from the UKDA dataset where the number in the name indicates the number of residents; Res2b is the residence with the same appliances as the SD and CREST models, having two residents. The qualitative properties of AMDLP from the real residences (Figure 70) are: gradual transition between trough and peak; at least, visually distinct mountain-like peaks; and continuity between the end of the plot and the beginning. The exception is a steep transition in Res1a which could be due to a scheduled device that operates at the time of day throughout the year.

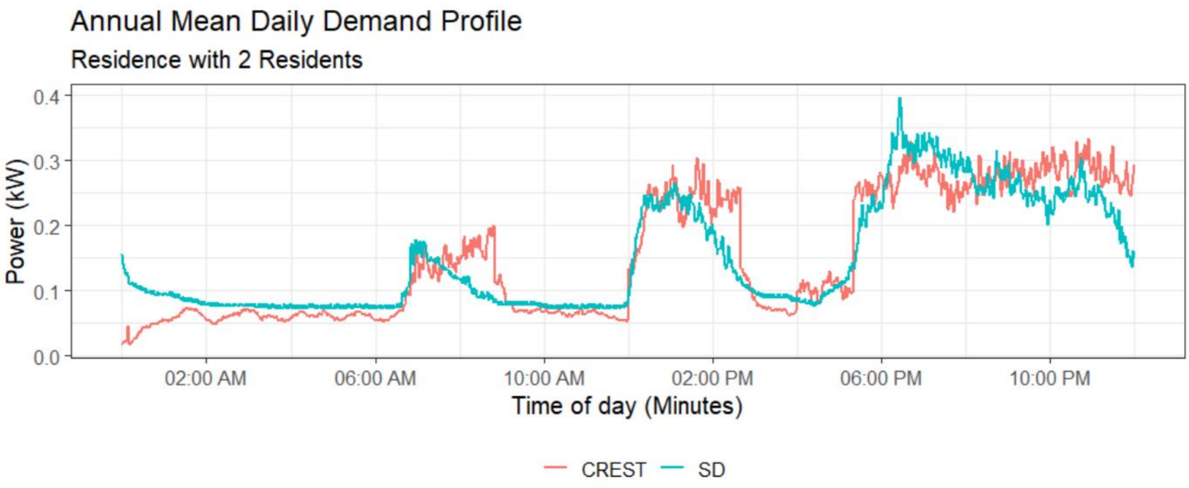

Figure 67 – Annual Mean Daily Load Profile for the CREST model and SD model for residences with 2 Residents

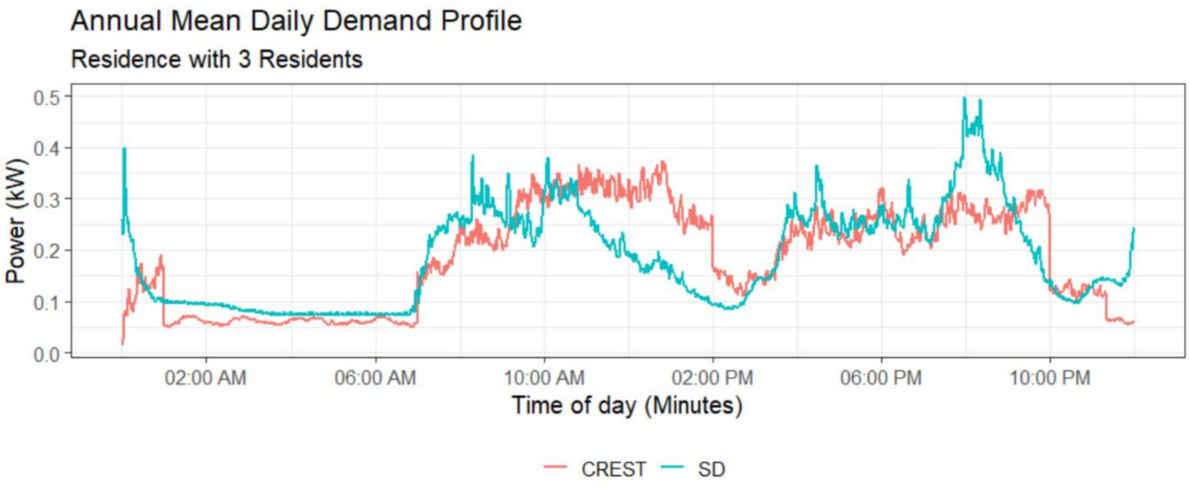

Figure 68 – Annual Mean Daily Load Profile for the CREST model and SD model for residence with 3 Residents

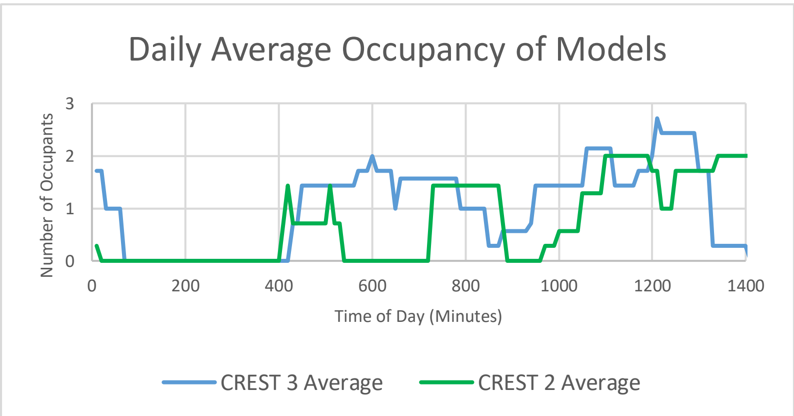

Figure 69 – Occupancy of the residences used in the CREST and SD model; for residences with 2 and 3 residents

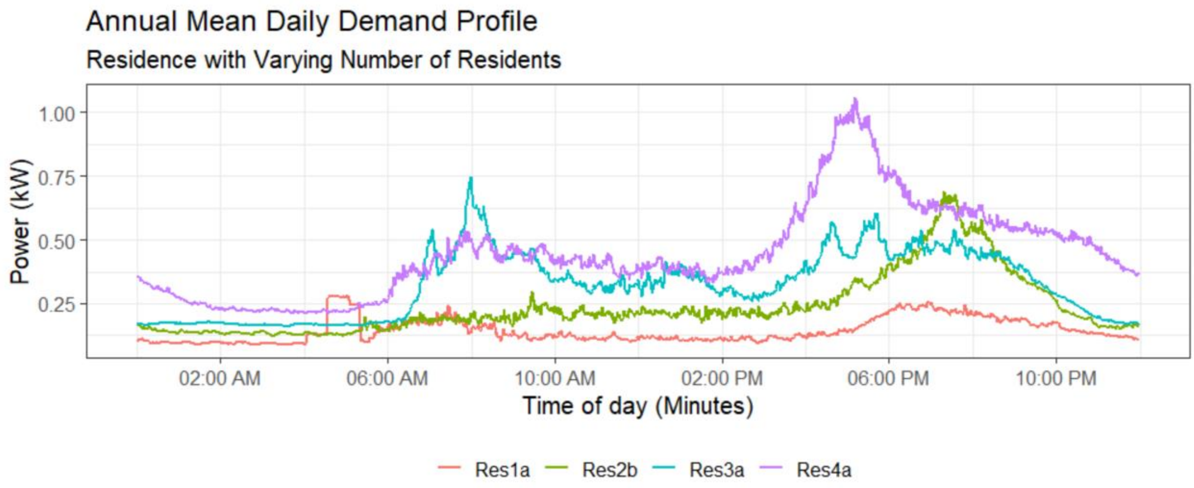

Figure 70 – Annual Mean Daily Load Profile from UKDA dataset for residences with a different number of residents

Visual-quantitative comparison of the AMDLP in Figure 67 and Figure 68 are generally similar in terms of power consumption and time. Where the power consumption from the SD model falls short of the CREST model, it compensates for it in other peaks. Moreover, the difference between the two models on total power consumed in a year is less than 1%: 0.67%, 0.78% and 0.5% for residences with 1, 2 and 3 residents respectively (see Figure 63). For qualitative comparison with the identified properties of real residences, the CREST model is steeper during occupancy transition, flatter during active occupancy and lacks visual continuity from the end to the beginning of the plot. Therefore, it seems the SD model behaves more similar to the real residences than the CREST model.

6.4.1.3 *Hourly Load Duration Curve (HLDC)*

Similar to the AMDLP, the HLDC is another way to summarise the load profile over a long duration by plotting the average hourly load per time in descending order as shown in Figure 71, Figure 72 and Figure 73. Figure 71 and Figure 72 show the HLDC of residences with two and three residents respectively, while Figure 73 shows the HLDC of real residences from the UKDA datasets. The plots have been separated to aid readability because the pair of plots in Figure 71 and Figure 72 follow each other closely. The qualitative property of the real residences (Figure 73) to be used for qualitative comparison is that the HLDC are smooth, each like a single curved line; not angled straight lines.

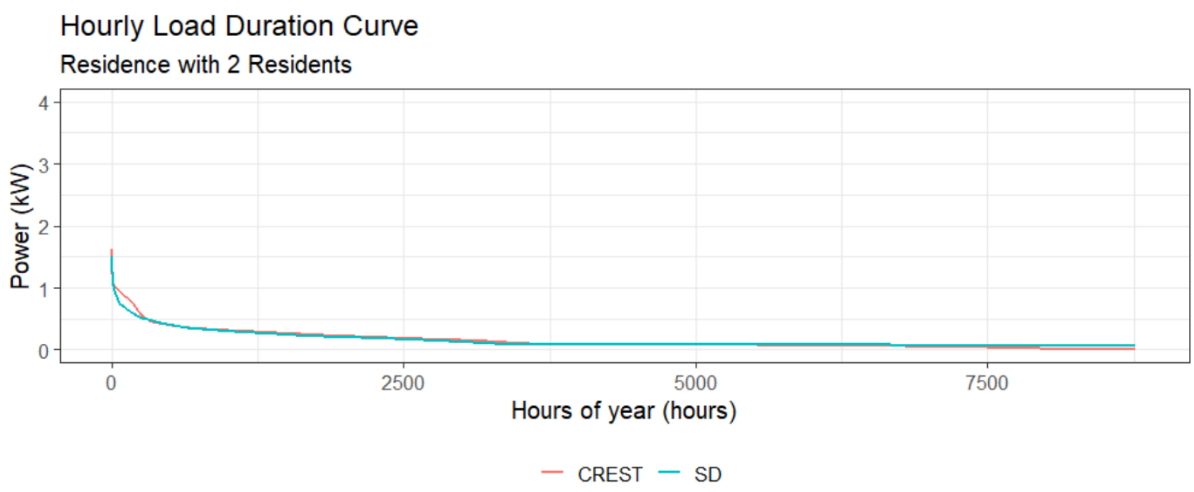

Figure 71 – Hourly Load Duration Curve for the CREST model and SD model for residence with 2 residents

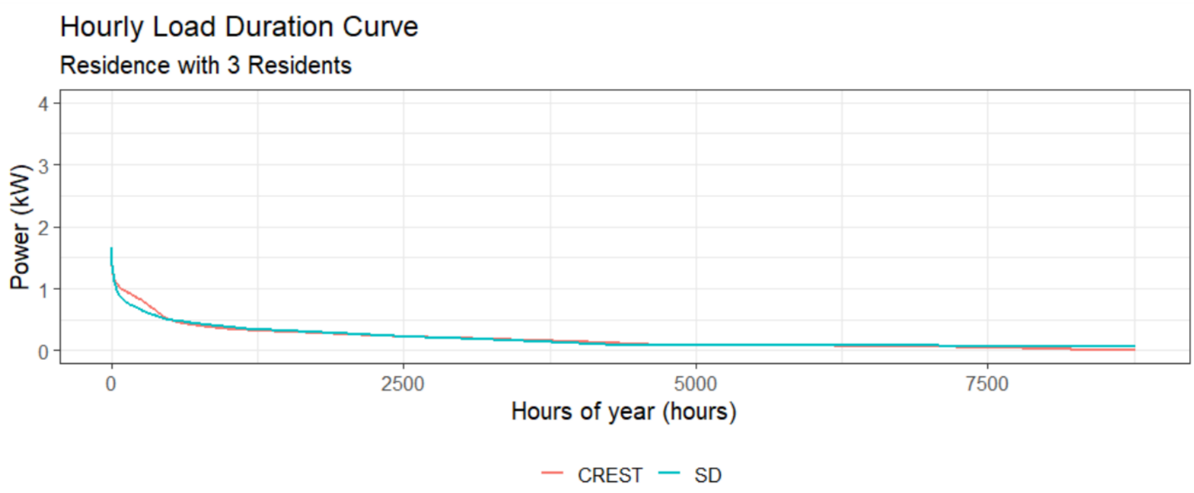

Figure 72 – Hourly Load Duration Curve for the CREST model and SD model for residence with 3 residents

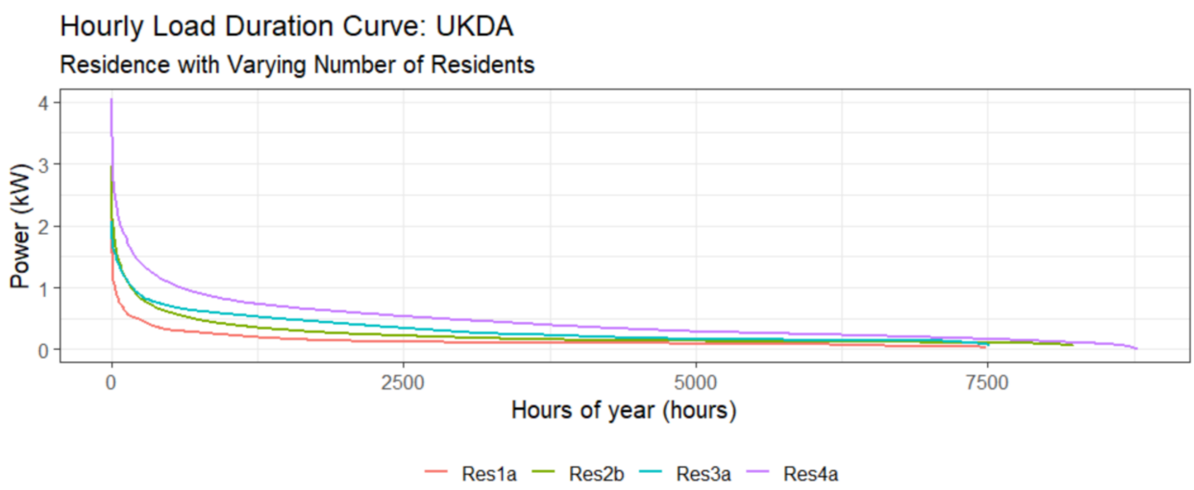

Figure 73 – Hourly Load Duration Curve from UKDA dataset for residence with varying number of residents

For the visual-quantitative comparison in Figure 71 and Figure 72, the SD model approximates the CREST model well. Qualitatively, the SD model appears smoother than the CREST model, and that makes the SD model more similar to the real measurements of Figure 73.

6.4.1.4 *Summarising Behaviour Comparison*

In summary, the SD models behave like the CREST models with the same number of residents in terms of load profile, AMDLP and HLDC. Where the SD model deviates from the CREST model, it behaves more like real residences from the UKDA dataset than the CREST model.

6.4.2 Output on Appliances

In addition to the residential load, other outputs from the simulation include the distribution of appliances' activation and operation. Figure 74 and Figure 75 show the distribution of the operation of appliances in a day over a year from the output of the SD model for a residence with two and three residents respectively; and these can be used as probability distributions. The distributions fall within active occupancy period except the washing machine which is semi-automatic and only requires to be setup and started within active occupancy. In other simulation models reviewed (Section 6.2.4), functionally similar probability distributions are extracted from TUD and provided as input to the models, whereas it is an output in these SD models; Figure 76 shows an example of input to the CREST model. Serving a similar function as input in the SD model is a single value: average frequency of appliance use. Having these distributions and their derivatives as input makes the other models more coupled to historic correlations, while the SD model is less coupled to historic correlations. Furthermore, these outputs from the SD model could be used for analysis or as input to other simulations.

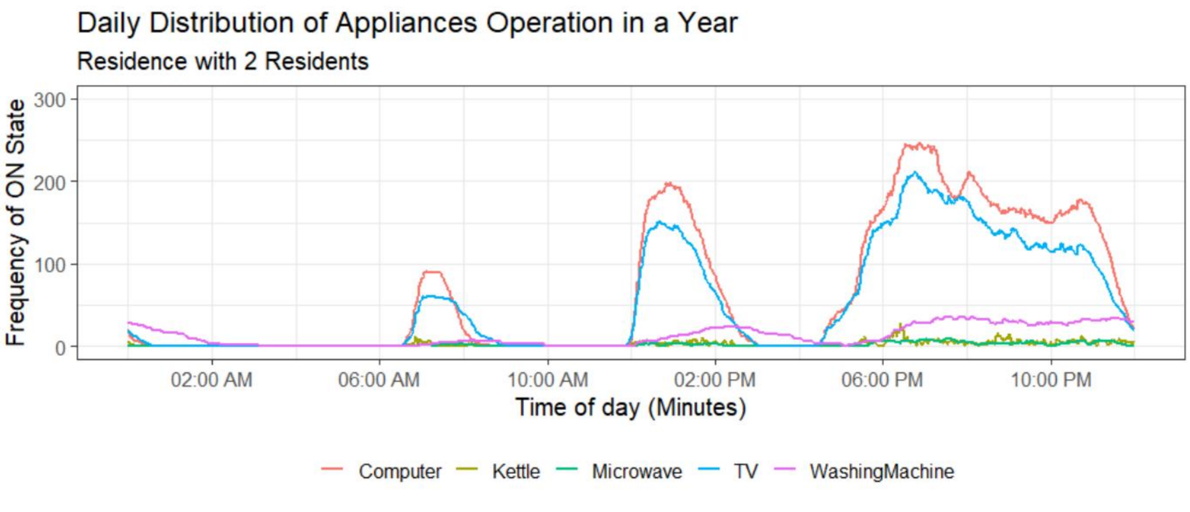

Figure 74 – Distribution of appliance operation in a day over a year, from SD model with 2 residents

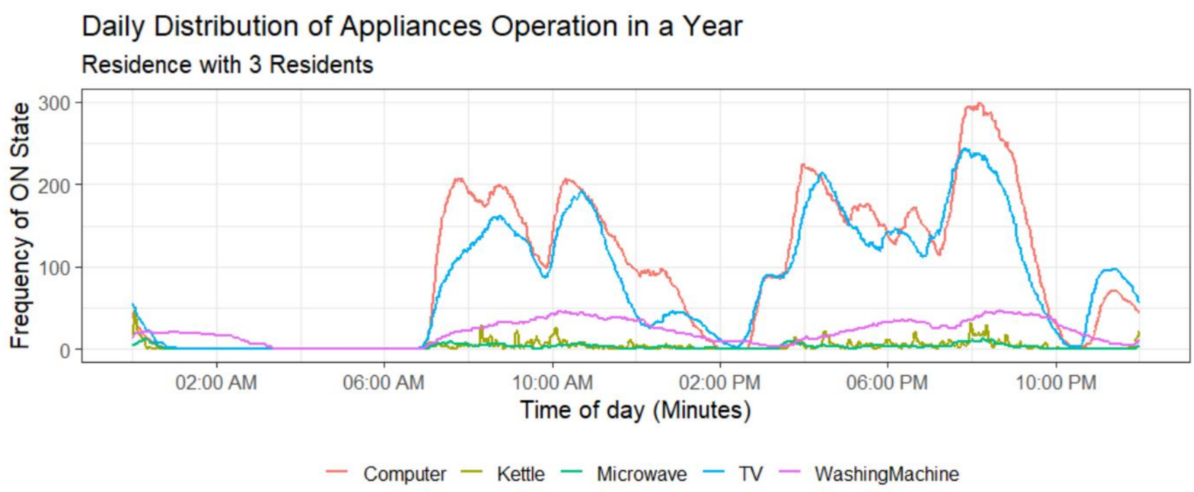

Figure 75 – Distribution of appliance operation in a day over a year, from SD model with 3 residents

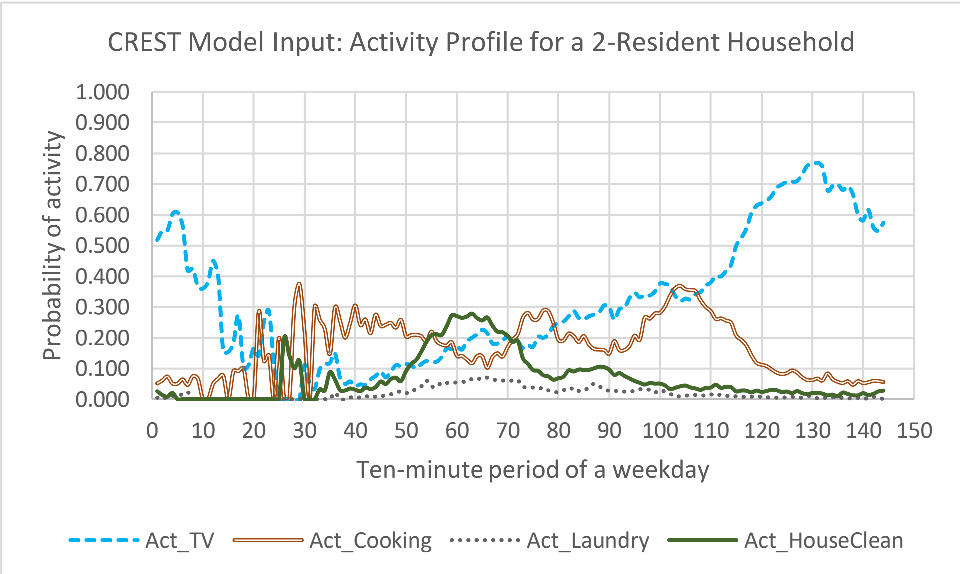

Figure 76 – Input to CREST model showing probability of activities as proportion of households where at least one occupant is engaged in a particular activity during a particular ten-minute period

6.4.3 Complexity

6.4.3.1 *System Complexity*

There are two sources of complexity in any system [72]: detailed complexity which arises from aggregation of system components linearly; and dynamic complexity which arises from relationships among system components which are characterised by feedbacks, non-linearity and delays. The detailed complexity of the SD model is proportional to the number of elements in the system, e.g. residents and appliances. On the other hand, the dynamic complexity is determined mainly by the dependencies and constraints within the system as formulated in the system's logic.

The two types of complexity are not necessarily complementary; e.g. when a residence with two residents has one of its two (non-sharable) kettles removed from the system, then one resident would have to wait for the other to finish using the kettle before using it if they both plan to use it at the same time. In this example, the detailed complexity reduced because there are fewer appliances, but the dynamic complexity increased because of the increased dependency between the activities of the residents. Therefore, the multiple constraints and conditions required before activating an appliance in the SD model can be considered as contributors to dynamic complexity.

Stochasticity from noise parameters could increase complexity in terms of uncertainty about the value of the associated parameter, and this may be considered dynamic complexity because the noise parameters affect time variables (occupancy and appliance operation duration), the effect of which is a delay or advancement of the activation of an appliance in time. Delay or advancement in timing has cascading/ripple effects in time which alters the dependencies in the future, but not infinitely.

6.4.3.2 *Computational Complexity and Cost*

Computational cost can be expressed in terms of time taken to run a model, and it is directly proportional to the complexity of the model. There are two levels to evaluate and compare the computational complexity associated with the models. The first is at the level of algorithm, and the second is at the level of the implemented model. Complexity of algorithms can be estimated using the Big-O notation which expresses the rate of growth of run time relative to the size of input. On the other hand, implemented models are impacted by the inefficiencies of the software platforms they are built on, and therefore the actual time taken to run a model can represent the cost.

The Big-O complexity of the algorithms for SD and CREST is linear because the number of operations increase as the input size increases; input could be time duration of the simulation. This is based on the two models ran for a duration of 4, 36, and 365 days, being approximate factors of 365. The time taken to simulate a residence (having the same appliances) with three residents for the duration of a year (525,600 time-steps) is 186 seconds and 660 seconds for SD and CREST models respectively. The time was measured using a stopwatch and inline python code respectively. It should be noted that while the SD model is implemented in Vensim with some input read from Microsoft Excel, the CREST model was implemented in Microsoft Excel (VBA) for daily simulations and a Python script was written to automate the daily simulations for a year. Therefore, whilst both models are linear, the SD model has a lower rate of growth and is computationally less costly compared to the CREST model in the current implementation.

6.4.4 Evaluation of the Model's Aims

The two aims of the SD simulation model are to be realistic and minimise historic coupling. The SD model has been shown to be realistic to the extent that it behaves similar to the CREST model and measurements from real residences of the UKDA dataset, in Section 6.4.1.

Whereas most of the reviewed simulation models (Section 6.2.4) are driven by historic probabilities of appliance use, the SD model is driven by the average frequency of an appliance use, and that makes the SD model less historically coupled or fitted. This is because the historic probabilities are typically generated from high resolution data of activities (TUD) which makes it sensitive to granular change in the time and individuals/residents in the sample population, whereas average frequency of appliance use is a summary statistic that is less sensitive to granular changes. Moreover, multiple TUD for the same activity (or appliance use) could summarise to the same average frequency of appliance use. Similarly, some of the reviewed models also describe occupancy of residents from historic probabilities derived from TUD, whereas the SD model allows occupancy to be described as a simple binary for times of weekday or weekend.

6.4.5 Some Benefits of the SD Model

Compared to some of the reviewed models, the benefits of the SD model include being more cost effective, more interpretable and enabling trans-disciplinary research. Interpretability aims to simplify translation of the main variables between the model and real world; which should aid policy research. Enabling trans-disciplinary research refers to employing a modelling language that is not discipline-specific.

Compared to models based on TUD, the SD model could be less expensive to collect data on appliance use, assuming data collection is part of the model's cost. Unlike TUD which is resource intensive in terms of cost and person-time, the average frequency of appliance use can be estimated from asking a single question about a household appliance. Since TUD is also scarce, average frequency – estimated or collected – could facilitate empirically grounded models. Computationally, it may also be simpler to calculate average frequency of appliance use compared to generating probability distribution of appliance use from TUD. Furthermore, output from the SD model can be used as probabilities of appliance use as shown in Section 6.4.2.

The SD model is more interpretable than other reviewed models because its driving input (average frequency of appliance use) is easier to translate to the real world than the more abstract driving input (probabilities) of the other models. Being more interpretable could simplify simulating real residences in the model and extracting insight from the model to a residence in the real world; e.g. a limit to average or total use of an appliance in a duration.

Finally, the model enables trans-disciplinary research by using the generic language of systems in the form of CLD and SFD. Furthermore, the use of SFD eases integration with other SFD models as long as the models share a common variable, regardless of disciplinary boundaries. Whereas integration between models could be achieved via a common interface (for inputs and outputs), integration among SD models makes the interface seamless, while allowing for interaction between variables of the models, including endogenous variables. Therefore, common variables are not limited to those that are input in one model and an output in the other model.

6.5 Conclusion

This chapter addressed the fifth thesis objective, which is to develop a valid simulation model of a demand-side energy system from the bottom-up using SD. The model generates synthetic residential load based on the SD modelling process from Chapter 3. The model was conceptualised as a CLD based on literature and reasonable assumptions, and subsequently, a simulation model was presented as a SFD. Both the conceptual and simulation models address the concerns of SD validity tests. The output load from the SD model was compared to output from the well validated CREST model, then both were compared to residential load measurement from real residences (UKDA), and the behaviour of the SD model was found to be realistic. Therefore, output from the SD model could be used as input to other simulations like other synthetic simulation models. Furthermore, distribution of appliance-use was explored as an output from the SD model. In conclusion, the complexity of the SD model and some benefits were discussed.

The demand-side model from this chapter will be integrated with the SD supply-side model from Chapter 4, in Chapter 8. Furthermore, Chapter 8 will also explore scaling the demand-side model beyond a single residence to a community or group of residences. Before then, the demand-side model will be integrated with a Demand Side Management (DSM) subsystem and then applied in decision-making analyses in the next chapter.

7 Decision-making Analysis using Demand-side SD Models

7.1 Introduction

The aim of this chapter is to demonstrate the use of an SD demand-side model in decision-making analyses, which is the sixth thesis objective. The resulting model is a RES with Demand Side Management (DSM) capabilities. The literature of DSM is reviewed, especially concerning a variety of DSM strategies and how they are analysed and assessed for decision-making. Gaps and opportunities from the literature inform the design of the case-study. Then the demand-side SD model created in Chapter 6 is integrated with a DSM subsystem. Four DSM strategies are compared in the same residence, which correspond to five scenarios, including a base scenario.

7.2 Literature Review

7.2.1 Demand Side Management

Many of the challenges faced by smart grids and traditional grids can be reduced by gaining more control over energy demand. Some of the perennial challenges of all power grids include underutilisation of infrastructure (generation capacity, transmission lines, distribution networks) and mismatch between supply and demand (especially peak load) [324]. Another major challenge is uncertainty which is introduced by intermittency of renewables, decentralisation of power systems and the emergence of new loads like electric vehicles [325], [326].

Demand Side Management (DSM) is any measure taken on the demand-side of an energy system to address challenges in the energy system ranging from installing more efficient loads, to sophisticated dynamic load management systems [327], [328]. Whilst DSM has been traditionally driven by (the needs of) utility companies to control customers' energy use [328], (the needs of) customers are also being considered [327]; for example, customer convenience is explicitly considered in designing DSM solutions in [309], [329].

The benefits of DSM may be categorised into benefits for utility companies and for customers. Some of the benefits for utility companies include reduction in overall costs (investment in capacity), reduction of carbon emissions levels, efficiency (optimum utilisation) and improved resilience to intermittent sources and distributed generation [324]–[326], [328]. The benefits for the customer include monetary savings, though it has not been found to be incentivising [329].

DSM may be categorised as illustrated in Figure 77 with a focus towards Direct Load Control [327], [330], [331]. The top-level categories are Energy Efficiency, Demand Response (DR) and Spinning Reserve. Direct Load Control, which aims to shape the load profile, may be further divided according to the targeted shape into: peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape.

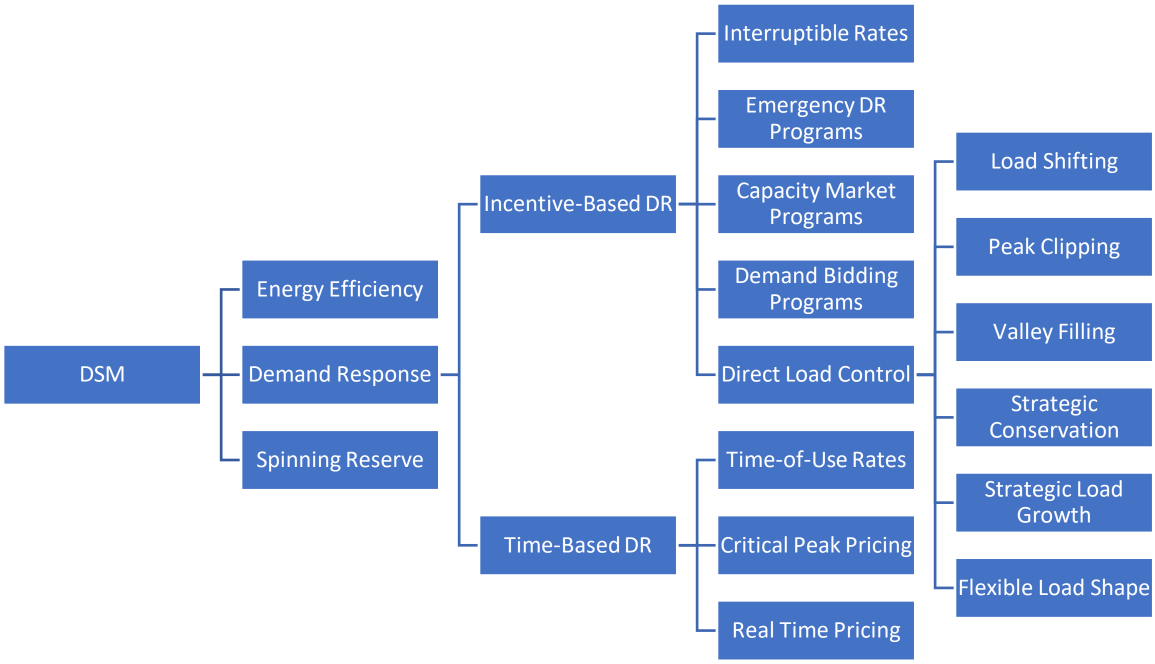

Figure 77 – Classification of DSM focusing on Demand Response and Direct Load Control

Energy Efficiency is the most effective DSM because it saves energy and emissions regardless of when the appliances are operated, whereas the other DSM often require shifting the appliances in time [327]. Load shifting was the most widely applied technique of load management as at the 1980s [331], and it appears to remain so either via Direct Load Control or Time-of-Use (ToU) Rates. Load Shifting relies on the flexibility to run certain appliances within specified periods. The DSM model in this chapter shall focus on Load Shifting. Whilst [329] found that monetary savings are not incentivising, [326] posits that smart pricing can encourage more efficient energy consumption.

7.2.2 State of the Art

Given the need for DSM and its benefits, there is a need to explore DR strategies in simulation environments; this study is interested in the bottom-up simulation of DR in residences. The literature is dominated by simulations of Load Shifting strategies, which are usually explored with the aim to determine optimum strategies. In majority of cases, load is shifted to minimise energy cost when the focus of the DR is residential consumers, or to minimise peak demand for energy when the focus of the DR is the supplying companies. Most Load Shifting strategies are implemented at appliance level and rely on external signals, except lighting and cooling which may be simply turned off periodically as in [309], [329], [332].

Load Shifting strategies are typically implemented in an Energy Management System (EMS) as optimisation problems with defined objectives and constraints. The two dominant objectives are to minimise cost, as in [326], [328], [333]–[335], and to minimise aggregate demand and peak demand, as in [336], [337]. Nonetheless, generic objective functions to shift load had been proposed in [324]. The use of price has at least two limitations, which includes that it does not reflect the infrastructure status, as well as it offers limited customer elasticity (ability of customers to change demand based on price). Both limitations can be addressed by Physical DR [327]; physical DR corresponds to Direct Load Control and Emergency DR Programs in Figure 77.

Whilst most DR are implemented at appliance level, the appliances have been categorised differently. In most cases, appliances were explicitly categorised into shiftable and non-shiftable appliances [324], [326], [328], [329], or implicitly in [333]–[337]. In other cases, appliances have been categorised into priority groups of the customers [309], or an agnostic approach to appliances was adopted by focusing on an attached control unit which controls an appliance [332].

Most of the scenarios analysed in the literature pertain to problems of electric utilities like reducing peak loads [309], [329], [332], [337], reducing the impact of black-outs [309] or system failure [332] and short frequency dips [332]. Over the years, the benefit of DSM explored in simulation models has been gradually expanding from the benefits for utility companies towards considering their customers. The benefits considered can be grouped into economic, social and cultural benefits, but the complexity of achieving social objectives in DSM has been acknowledged in [326]. Cultural benefits can be assumed to be complex too because they are often assumed instead of modelled. The economic benefit is mainly cost savings [326], [328], [329], [333], [334], while the social benefits include fairness of cost savings in a community [334], [338] and privacy [333], [335], and the cultural benefits include customer convenience. The trend points to more interest in fairness of economic compensation, not just compensation. Another interesting concern is user privacy. As smart devices become ubiquitous, targeted campaigns and cyber-attacks become more prevalent; user security had been acknowledged as a concern a decade ago in [327].

Customer convenience is understood as preferences which include comfort and timeliness. In most of the cases reviewed, customer convenience was modelled as an assumed constraint in an optimisation problem and used to define scenarios. As a constraint, it has been modelled as a range of indoor temperature [328], [334], [337], customer-defined priority of appliances [309] or appliance runtime. As appliance runtime, it has been modelled as either a maximum time window [329], [332], or latest time [329], or crossing a specific time of day (e.g. 6 am) [329]. Convenience has also been associated with economic benefits; e.g. satisfaction level of residences has been reduced to monetary cost to residents in [333].

Beyond simulations, an open-source automated DR system has been specified and implemented by OpenADR [339], [340] based on a publisher-subscriber model in a distributed DR infrastructure. This allows manufactures to adopt OpenADR by making their appliances clients that can subscribe to a server which can host various DR programs.

7.2.3 Gaps and Opportunities

There are some gaps in the reviewed literature. All the above studies simulate hundreds and thousands of residences per simulation, not individual residences, with the exception of a scenario in [328]. This may be because their underlying load generation models were validated against – and therefore realistic only to – a cluster of residences, or perhaps because they aim to address problems from the perspective of utility companies. Consequently, these studies do not explore the dynamics between appliances and residents at the residential level, including [328] where a single residence was simulated. Whilst dependency among appliances has been acknowledged in the literature and implicitly modelled in probability distributions of appliance use, no implementation was found that made dependency of loads an explicit description of the model. This study focuses on a single residence at a time, which could enable residents to gain insight and make decisions about their energy consumption.

Another gap in the literature is a way to measure and visualise the convenience of residents in the simulation, which could also be compared across scenarios. Existing literature has defined customer convenience but then assumed values that are used as constraints in optimising for price or other objective functions. Moreover, due to the lack of residence-level dynamics, convenience of residents has been specified homogenously at communal/group level. Consequently, existing simulations have not attempted to answer questions like how much inconvenience would a resident (or average resident in a residence) endure if they define their convenience in terms of a delay or deadline at a particular time of day. A bottom-up simulation of DR at residential level may be able to respond to these questions.

7.3 Methodology

7.3.1 Case-Study Aims

Based on the above, the focus of this case-study is on the exploration of DR in a SD simulation model of residential load. Unlike the reviewed DR models that consider clusters of residences rather than single residences, this paper explores scenarios of DR strategies at the level of a single residence. Moreover, this requires that the model describe the dependence between residents and appliances, as was done in Chapter 6. In addition to the residents' convenience, typical indicators of interest like peak load and money saved shall be explored. Therefore, the aims of this case-study are four:

1. Create a valid DR simulation at the residential-level where interdependence among appliances, residents and external DR signals is modelled;
2. Explore consumer convenience in different DR strategies;
3. Analyse peak load in a year by different DR strategies;
4. Analyse money saved by different DR strategies.

7.3.2 Case-Study Design

To achieve its aims, the case-study can be described using the SA framework explained in Chapter 3 (and implemented in Chapter 5). The case-study design is presented in Figure 78, and the two steps of the design are: define the purpose of the study and identify required variables. To elaborate on the purpose, scenarios will be specified in Section 7.3.3. The simulation model will be built based on the modelling process in Chapter 3, and the Performance Indicators will be calculated.

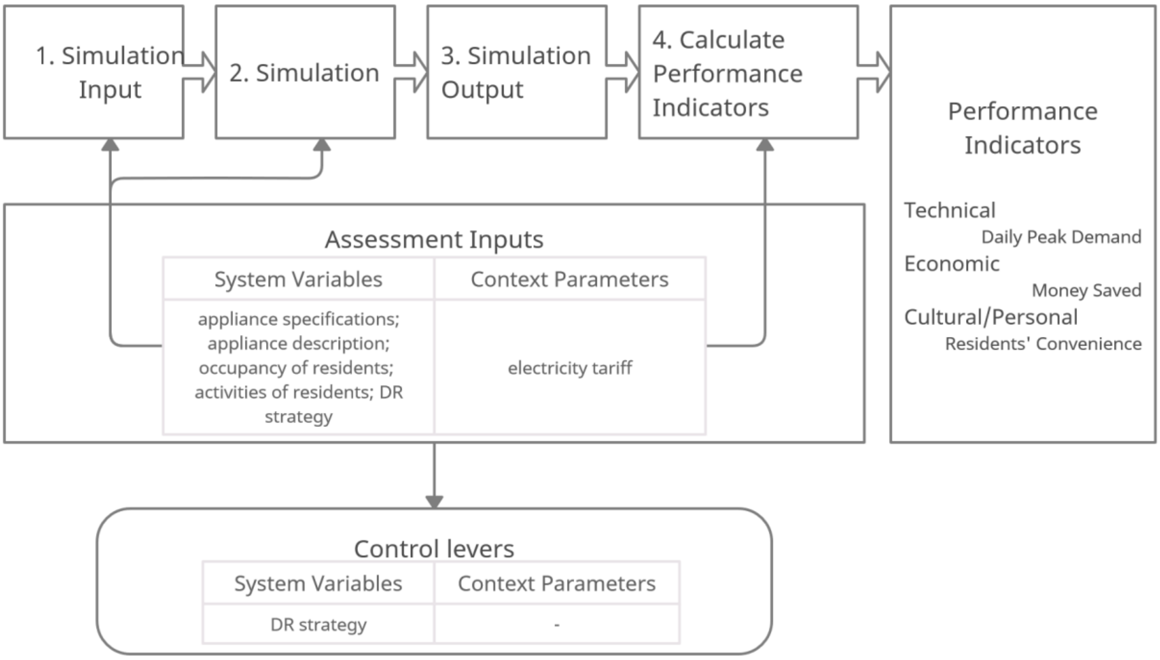

Figure 78 – Chapter 7 case-study design

Looking at Figure 78, the study basically explores the effects of different DR strategies on daily peak demand, money saved and residents' convenience. Some of the relevant variables are DR Strategy, appliance specifications (e.g. mean cycle duration, power consumption), occupancy of residents, activities of residents (e.g. frequency of activity use), electricity tariff and the description of the operation of appliances in the simulation. The Performance Indicators and simulation model will be discussed in subsequent sections.

7.3.3 Scenarios and Performance Indicators

The model is based on a residence with three occupants and the appliances in Table 28. Whilst 2-person residences are the most common in the UK as at 2020 [341], a residence with three occupants provides more dynamic complexity because of more dependency relationships between the appliances and the residents. Three (semi-automatic) appliances are on the DR program: washing machine, drying machine and dishwasher.

Appliance	Quantity	On DR	Dependency	Mean Cycle Duration (minutes)	Cycles per Day
Fridge freezer	1	No	-	22	24 x 1.2
Personal computer	1	No	-	60	6 x 1.2

TV	1	No	-	73	4 x 1.2
Microwave Oven	1	No	-	30	0.3 x 1.2
Kettle	1	No	-	3	4.2 x 1.2
Washing machine	1	Yes	-	138	0.5 x 1.2
Dryer	1	Yes	Washing machine	60	0.5 x 1.2
Dishwasher	1	Yes	-	60	0.5 x 1.2
LED Lights	5	No	-	Depends on room occupancy	

Table 28 – Appliances in the simulation model and highlighting the appliances on DR

A baseline scenario where DR is not active was simulated. Then four DR scenarios were defined based on the four DR strategies, corresponding to four tariffs. Furthermore, to make the comparison between DR scenarios more comparable, the same random delays are generated in all the scenarios by using the same seed in the random number generator. The random delay is generated daily, while each DR appliance runs about once in two days on average (see Table 28; 1.2 is the cycling factor for three residents as explained in Chapter 6).

There are two groups of Performance Indicators to compare the scenarios. The first group compares the baseline scenario to the four DR scenarios, and the two metrics are Daily Peak Demand and Money Saved. The second group compares among the four DR scenarios, and the focus is on comparing convenience of residents. See Table 29 for summary; convenience is measured using delay, Delay Duration Profile and Delay Time Profile.

Scenarios	Is DR Active?	Performance Indicator
Baseline	No	Daily Peak Demand; Money Saved
Economy 7	Yes	Delay; Delay Duration Profile; Delay Time Profile
TIDE		
Economy 10		
Economy 10S		

Table 29 – Simulation scenarios and indicators

7.3.4 Convenience

Based on the reviewed literature, convenience has been defined in terms of time in two broad categories. The first is as a 'delay' or duration between when the appliance is set up and when the appliance is turned on, for instance, a dishwasher may take 3 hours after being loaded compared to 5 hours. The second is in terms of whether the appliance crosses specific times of day between set-up and turn-on, for instance, whether the dishwasher runs by 6:00 am after it had been loaded. However, as noted in Sections 7.2.2 and 7.2.3, previous simulation models of DR were not designed in a way that consumer convenience can be measured. Instead, consumer convenience was assumed a value and incorporated into the models as constraint. This study proposes a way to measure and visualise convenience of residents.

Convenience was measured and visualised using two proposed metrics: Delay Duration Profile (DDP) and Delay Time Profile (DTP). Both DDP and DTP quantify inconvenience, and therefore convenience would be the inverse. The DDP quantifies the number of times a specific duration of the delay is exceeded in the simulation period, by plotting delay duration against frequency of delays that exceed the delay duration. On the other hand, the DTP quantifies the number of times a particular time of day falls during a delay, by plotting time of day against frequency of delays at that time of day. DDP and DTP can be used to make decisions about convenience by residents, because both are mathematical functions of the residents' preferences. Residents' preferences are defined in terms of maximum tolerable delay duration for DDP and intolerable time of day to have a delay for DTP. Functions for DDP and DTP are generated per appliance per residence, and therefore, can be considered properties of an appliance in the particular residence in which they are generated.

Convenience and preferences are important because cultural preferences can undermine any effort at a solution despite a good performance economically, environmentally or technically. It has been shown that residences decided to use increased and expensive energy so they can have 'quality family time' [12]. Also, it had already been mentioned that monetary savings have not incentivised more efficient energy use [329], which could be due to cultural preferences. Furthermore, it had been mentioned that cultural preferences undermined the assumption that higher income would lead to use of more efficient cooking energy, where higher income led to a wider choice of energy source instead [10]. Finally, it has also been argued that the failure of adoption of efficient stoves, despite interventions for over three decades, is due to disregard for cultural preference of the users of the technology [2].

Ultimately, the cheapest, most efficient and most environmentally friendly solution may not be used if the users have options and the solution does not align with their cultural preferences. In the case of DR, residents would opt out of DR strategies that are not convenient.

Therefore, DDP and DTP are to be used for making decisions about convenience of DR strategies on appliance-use at residential-level. Since DDP and DTP are functions of residents' schedules and preferences, they require additional input from the decision-maker to resolve to a value. They could enable residents to make decisions on which DR strategies to adopt, given their preferences. Since they measure residents' convenience, DDP and DTP can be considered cultural indicators or tools.

7.3.5 Model Conception

The DR model is based on the high-resolution model of residential appliance load from Chapter 6, which is a bottom-up demand-side SD simulation that generates realistic residential load based on interaction between the activities of residents and appliances, and the feedbacks that exist among them; see Section 6.3.2. To simulate DR, the residential model will be modified by integrating a DR subsystem which is the main focus of modelling in this chapter, and discussed in this section.

To model and integrate the DR subsystem to the load generation model, the modelling process for modification used in Chapter 4 (Figure 12) will be utilised. Semi-automatic appliances (like washing machine, dishwasher and drying machine) are subjected to DR because of their flexibility in terms of operation time without infringing on user comfort, as discussed in Section 7.2.2 . Whilst consumer electronics (with batteries) like laptops could be charged at flexible times without infringing on comfort as well, they are not considered for DR in this study because the focus is on DR that is controlled centrally (based on the state of the network or local grid controller), rather than by volition of individual residents, as one would decide when to use battery or mains. Moreover, consumer electronics with battery were not included in [329] because their energy impact is considered low.

The DR control is achieved via a generic DR Signal which could represent the DR signal in the OpenADR framework as in [339], [340], or feedback from the network or local controller as in [332], or a generic objective function as in [324] or even peak tariffs in Time-of-Use tariff. Being exogenous to the residential model, a DR signal could be generated by feedback from an electricity network or other algorithms which determine the optimal times to operate the DR appliances.

The DR subsystem can be divided into exogenous and endogenous variables. The exogenous variables are DR Signal and DR Mode, while the endogenous variables include DR Schedule X, DR Signal X and DR Agent X; where X is an appliance to which the variables are modelling. Therefore, exogenous variables are common to all appliances in a residence, while the endogenous variables are specific to appliances. Consequently, the endogenous variables can conceptually model a physical DR device dedicated to an appliance. Figure 79 illustrates the relationship between the DR subsystem and other system components (Activity Timer nX and Appliance X) from the existing load generation model (from Chapter 6). Specific variables that are boxed are endogenous while those that are not boxed are exogenous. The DR subsystem groups all the endogenous DR variables in a larger box as a conceptual unit.

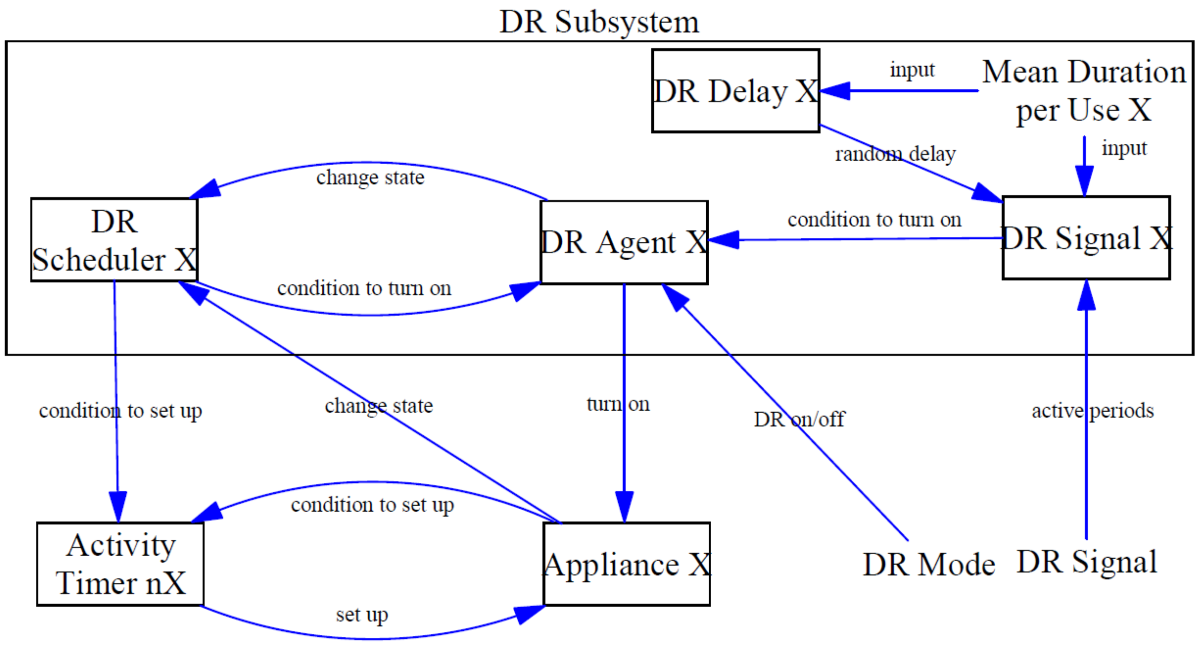

Figure 79 – CLD of components that form the DR subsystem and other system components

DR Signal indicates periods when DR is active. DR Mode indicates whether DR is activated or not. DR Delay X for each appliance X generates a random delay (per day) which delays DR Signal and results in DR Signal X; therefore, the former can be considered part of the latter. DR Signal X is utilised by DR Agent X in deciding whether appliance X can be turned on within the period/duty-cycle of DR Signal. DR Scheduler X keeps track of whether Appliance X has been set up (by a resident via Appliance X) for DR or not, DR Agent X turns on Appliance X at the appropriate time if X has been setup for DR, while DR Signal X indicates periods when it is appropriate for DR Agent X to turn on appliance X. DR Signal X considers DR Signal, the duration of appliance operation cycle, and a random delay for DR Agent from the earliest time to turn on X. These constitute the DR subsystem.

As a whole, the DR subsystem interacts with residents and appliances which are modelled as Activity Timer and Appliance respectively; where Activity Timer nX is an abstraction of the desire of Resident n to use Appliance X (from Chapter 6). The activity timers consider the occupancy of the resident and other constraints like available attention, but these dependencies are not shown in Figure 79. Therefore, for each appliance, there is an Activity Timer per occupant, a DR subsystem per appliance and the DR subsystem interacts with all the residents.

The structure in Figure 79 is consistent with a real feasible implementation of DR because the DR subsystem is similar to the control device discussed in [332] which connects to an appliance and controls the behaviour of the appliance based on external signals and the appliance's state; hence the feedback between the appliance and the DR subsystem. There is also feedback between the Appliance and the Activity Timer because the timer sets up the appliance (for DR Agent to turn on) and the state of the appliance (engaged or not) determines when Activity Timer can set it up and then reset Activity Timer. However, there is no direct feedback between the DR subsystem and Activity Timer (Resident), instead the feedback is via Appliance; DR subsystem provides the condition/state required by the Activity Timer to set up, Activity Timer sets up appliance, and Appliance eventually changes the state of the DR subsystem (via DR Scheduler).

7.3.6 Model Formulation

7.3.6.1 *Simulation Model*

DR Signal is implemented as a binary time-series input, where 1 indicates the earliest instance/period when it is permissible to operate a DR appliance; similar to a non-delayed DSM mode in [332]. DR Signal represents the DR strategies, which are based on a simple algorithm where DR is active when the ToU tariff is cheapest in a day. Other algorithms and objectives could be used to generate DR Signal.

Figure 80 shows a SFD where part of the DR subsystem attaches to an appliance and determines when the appliance turns on; Figure 80 is an elaboration of the concept in Figure 79, without Activity Timer X. Activate O1B*m* are the output/decision of Activity Timer B (where *m* is the resident number) indicating when to activate Appliance B. The simulation runs without DR when DR Mode is 0 (inactive), and in that case, activating an appliance simply turns on the appliance. On the other hand, when DR Mode is 1 (active), activating an appliance sets up the appliance for DR instead, and DR Agent eventually turns on the appliance at the appropriate time.

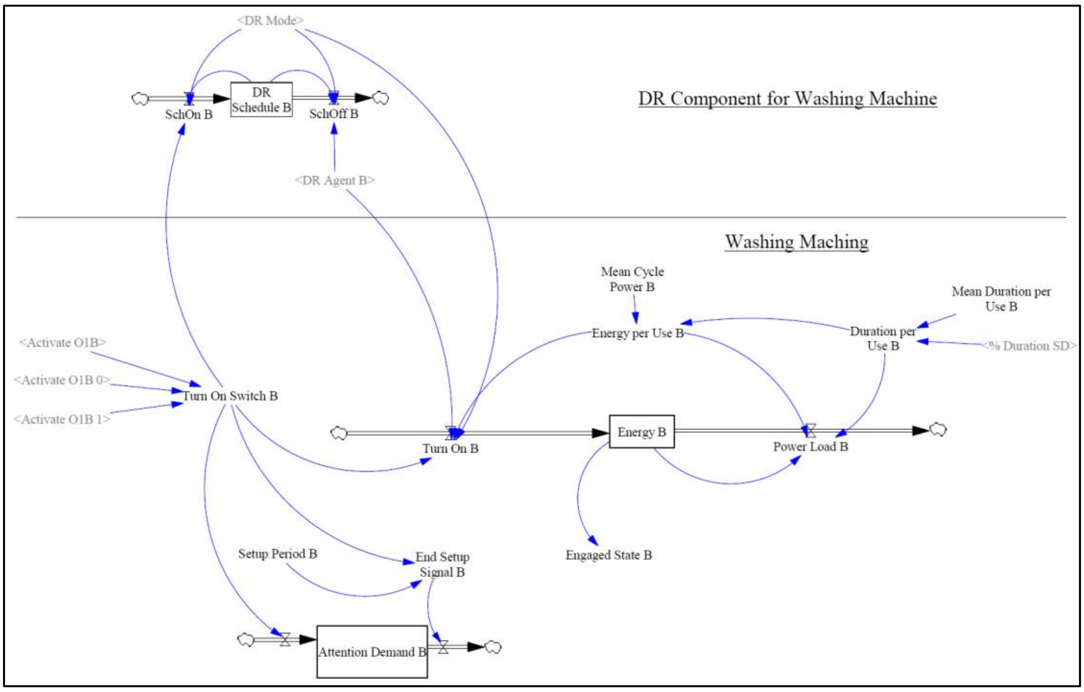

Figure 80 – SFD of appliance and DR subsystem with a horizontal demarcation between the two

The Scheduled State B was implemented as a binary switch which is set to 1 when an appliance has been set up (by Turn On Switch B) and set to 0 by DR Agent after the appliance has been turned on by DR Agent. Therefore, when DR Mode is 1 (active), there are two steps before an appliance turns on; the first step sets up the appliance then changes Scheduled State B to 1, and the second step runs the appliance then changes Scheduled State B to 0. These are the real-world equivalents of loading (or setting up) a washing machine to operate at the best time, as a first step, and then the machine 'automatically' (by DR Agent) operates when the 'best time' arrives, as a second step. Therefore, setting up the appliance still requires the attention and time of the resident, as is the case in the pre-DSM model in Chapter 6. Figure 81 shows the flowchart of the process.

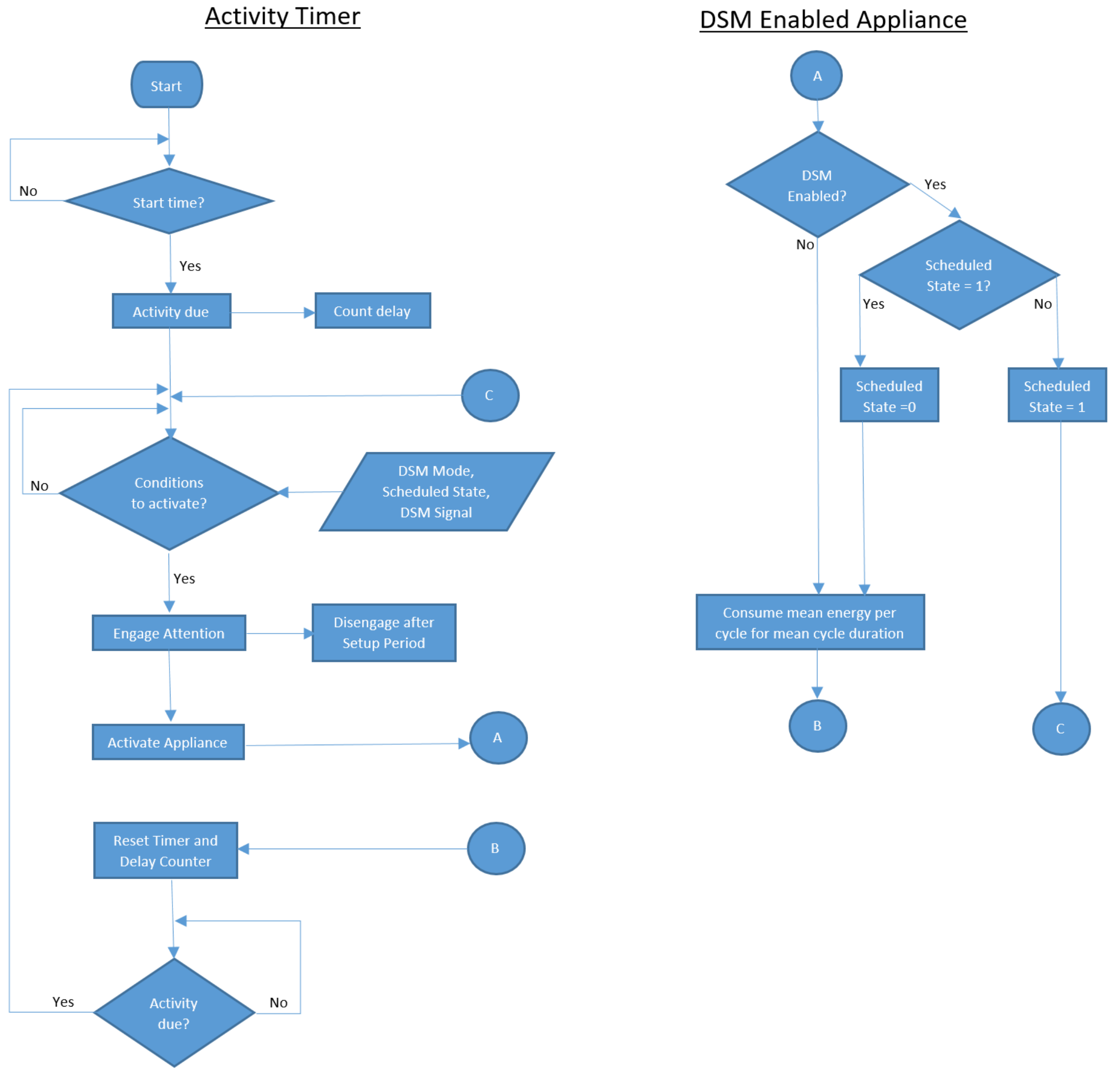

Figure 81 – Flow Chart of the DR Process

Whilst DR Signal is exogenous and shared by all appliances in a residence, DR Signal X is endogenous and specific to appliances. DR Signal X represents what the DR Signal could be for Appliance X after considering a random delay and the duration of the appliance cycle, which then enables DR Agent X to decide whether to turn on an appliance that has already been set-up for DR. Therefore, DR Signal X is also a time-series variable (like DR Signal) bound at the earliest by the delayed DR Signal (or DR Signal if DR Delay = 0), for the duration of DR Signal. Adding a random delay prior to activation of the appliances is important in DR to avoid situations where an electricity supplier may be overloaded with demand from residences at the beginning of the DR period, which could undermine the DR. However, there is no need to simulate scenarios without delay because the model is at residential level not at the level of the supplier, where the effect cannot be adequately simulated.

The operation of some appliances (e.g. drying machine) can be implemented to be dependent on the operation of other appliances (e.g. washing machine). It has been assumed that a drying machine will only be used if there is load that had been washed by the washing machine but not dried yet. A variable monitors the completed uses of the washing machine and it is used as a condition to turn on the drying machine, and this variable is reduced by 1 after a completed use of the drying machine. When the Activity Timer and other conditions are due for the drying machine to turn on but there are no washing sets that requires drying, Activity Timer is reset.

7.3.6.2 *Parameter Verification*

The setup period for an appliance has been maintained from the original model (Chapter 6) at 15 minutes, and this was assumed to be reasonable because it represents the duration of attention a resident commits to setting up rather than the actual time interacting with the appliance during the setup. All the semi-automatic appliances (washing machine, drying machine and dishwasher) use the same value. To generate DR Signals, the simple rule is for DR to be active when energy cost is cheapest in a tariff plan; after all the aim of variable price tariff plans is to encourage energy usage when it is cheapest. Four tariff plans were used for demonstration: Economy 7 which is cheapest between 00:00-07:00; Economy 10 which is cheapest between 22:00-08:00; Economy 10 Split which is cheapest between 20:00-22:00, 00:00-05:00 and 13:00-16:00; and TIDE Tariff of Green Energy UK which is a Time of Use (ToU) tariff that is cheapest between 23:00-06:00. The DR Programs and tariff names have been summarised in Table 30.

<table>
<tr><th>Tariff Name</th><th>Active DR Signals (Daily 24hr Period)</th><th>Source</th></tr>
<tr><td>Economy 7</td><td>00:00 – 07:00</td><td>npower [342]</td></tr>
<tr><td>TIDE</td><td>23:00 – 06:00</td><td>Green Energy UK [278]</td></tr>
<tr><td>Economy 10</td><td>22:00 – 08:00</td><td rowspan="2">Ovo Energy [343]</td></tr>
<tr><td>Economy 10 (Split)</td><td>20:00-22:00
00:00-05:00
13:00-16:00</td></tr>
</table>

Table 30 – Tariff names and corresponding DR Signals

Economy 7 and Economy 10 are common tariff names across electricity providers with 7 and 10 indicating the number of hours where price is cheapest per day; also known as off-peak hours. Economy 10 Split is also an Economy 10 tariff but split into time chunks; 'Split' was appended to differentiate. As mentioned, the resulting DR Signal is implemented as a binary time-series signal, where value of 1 means DR is active and 0 means DR is inactive.

Random Delay X has been implemented as a random variable from a normal distribution with a mean of 0 and standard deviation of a third of the mean appliance cycle time, bounded by a minimum of 0 to avoid negative delays.

7.3.6.3 *Extreme Conditions*

Does the model respond plausibly when DR Signal takes an extreme value? The two extreme values DR Signal could take is either being perpetually active or having brief pulses in active state. In the first case, the implication is that residents do not get to set up the appliances (which is done when DR Signal is inactive). The second case of the extreme value is unlikely to occur in a simulation but could occur in real systems when the brief pulses are noise. While these situations are unrealistic in a simulation, they are possible in the real-world.

In the first case, a logical validation could be included to disallow running the model if the duration of inactive DR Signal per day does not reach the duration required to setup a DR appliance. The implication is that an appliance that would typically run multiple times a day could be reduced to a minimum of once daily. In the second case of short active DR Signal, a logical validation could be included to turn on the appliance (not to setup) only when the DR Signal is active at the beginning and the expected end of the appliance's operation. Furthermore, there are two exceptional situations that could complicate the solution to the second case: when a burst signal appears exactly at the start and end; when DR signal is full of short bursts that never reach the duration of appliance operation. In real world application, DR Signal is the output from an algorithm, and it is expected that these extreme values will be addressed within the algorithm. In the case of this study, the DR Signals are controlled exogenous variables in a laboratory setting that do not present these extreme situations. Therefore, these extreme conditions are not addressed in the model.

7.4 Results and Discussions

7.4.1 Delay

Figure 82 shows the annual distribution of delays from the three DR appliances, each in the four DR scenarios. The x-axis shows appliances and corresponding DR scenarios: D for

Dishwasher; DM for Drying Machine; WM for Washing Machine; Eco7 for Economy7; TIDE for TIDE ToU; Eco10 for Economy10; Eco10S for Economy10 Split. The fill-colour of the boxplots, which are the rectangles with possible vertical lines above or below, also represents the appliance: red for Dishwasher; green for Drying Machine; and Blue for Washing Machine. For each Appliance-Scenario combination, Figure 82 shows the mean (yellow points), the boxplot (red, green and blue boxes) and the individual observations (blue points); the boxplot shows the interquantile range and the horizontal line in the box is the median. The shortest of the mean delay is 124 minutes on the Dishwasher (Eco10S), while the longest is 608 minutes on the Drying Machine (Eco7). All the upper quantiles are less than 1000 minutes.

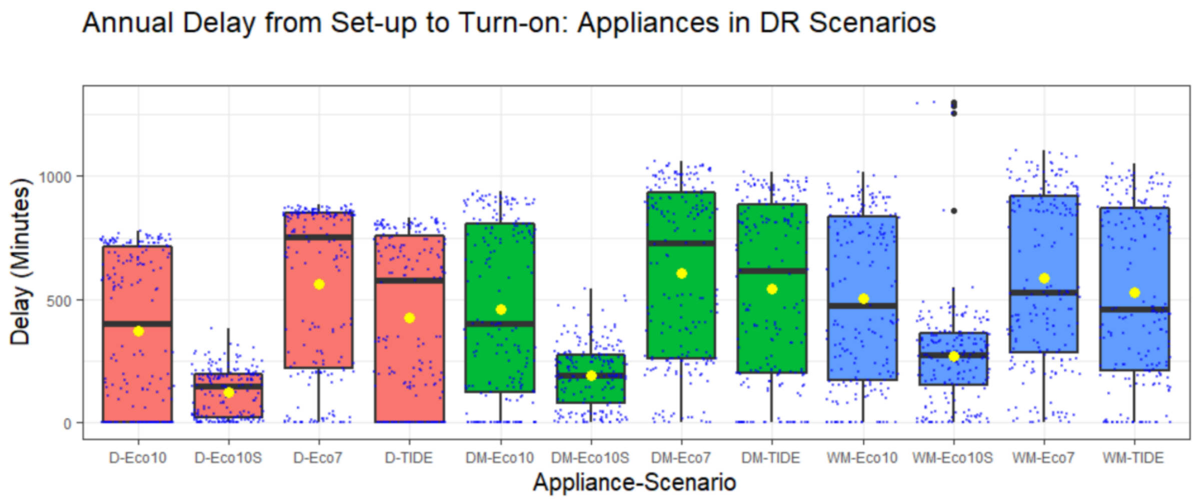

Figure 82 – Boxplots showing distribution of annual delay of Dishwasher (Red), Drying Machine (Green) and Washing Machine (Blue) in the four DR scenarios

Eco7 and TIDE have a DR period of 7 hours each, while Eco10 and Eco10S are 10 hours each. Therefore, three comparisons can be made: between individual scenarios of different hours; between scenarios of equal hours; and between appliances. Between scenarios of different hours, the mean and third quantile delays decrease as active DR hours increase; the delay increases from Economy 10 Split and Economy 10 with lower delay, to TIDE and Economy 7 having higher delay. This follows intuitively that it should take less time on average from setting-up/loading an appliance to having the appliance turn-on automatically if more time in a day is allotted for the appliance to be turned on. However, it does not explain the order observed when comparing between scenarios with the same DR hours.

Between scenarios of equal active DR hours, it seems the earlier start coincides with lower mean_delay: TIDE (23:00-06:00) has consistently lower mean delays than Economy 7 (00:00-07:00). Whilst Economy 10S (20:00-22:00, 00:00-05:00, 13:00-16:00) also consistently has lower mean delays than Economy 10 (22:00-08:00), though the difference could be because the DR hours are split. Therefore, the explanation for comparison between Economy 10S and Economy 10 is not conclusive. Moreover, the explanation for the difference between TIDE and Economy 7 is also preliminary because the assumption is that 'earlier' is relative to the start of the simulation and the mark of unit days which is 00:00. A more robust explanation may be explored in future work.

Finally, between appliances, the Dishwasher consistently shows lower delay (mean and upper quantile) than the Washing Machine and Drying Machine, but the latter two are not consistent in relation to each other. Whilst Drying Machine has the same mean cycle duration as the Dishwasher (60 minutes), it is operationally tied to Washing Machine cycles (138 minutes) before it gets set-up, and the mean frequency of cycles for all three appliances is about once in 2 days. Therefore, the faster Drying Machine is often set-up after the active DR hours where the slower Washing Machine was turned on, then delays until after the next active DR hours to be turned on.

More appliances would be required to determine whether mean cycle duration affects the delay, because whilst the Drying Machine and Dishwasher have the same mean cycle duration of 60 minutes, the Drying Machine depends on the Washing Machine for its operation which has a mean cycle duration of 138 minutes. Nonetheless, the distribution of delays may not be very useful for making decisions about convenience of residents.

7.4.2 Delay Duration Profile

Figure 83, Figure 84 and Figure 85 show the Delay Duration Profile (DDP) of three appliances, each in the four DR scenarios. The DDP quantifies convenience as the inverse of the number of times a specific duration of the delay is exceeded in a year. The plots cover the delay duration of up to a day (1440 minutes), while each of the appliances runs once every two days on average (see Section 7.3.3). For instance, taking the dishwasher in Figure 85, a delay of 750 minutes was exceeded more than 50 times in TIDE and more than 100 times in Economy 7, while it was exceeded less than 15 times in Economy 10 and not exceeded in Economy 10S. For each appliance, DR scenario with Economy 10S resulted in the least delay, followed by Economy 10, then TIDE, and finally Economy 7.

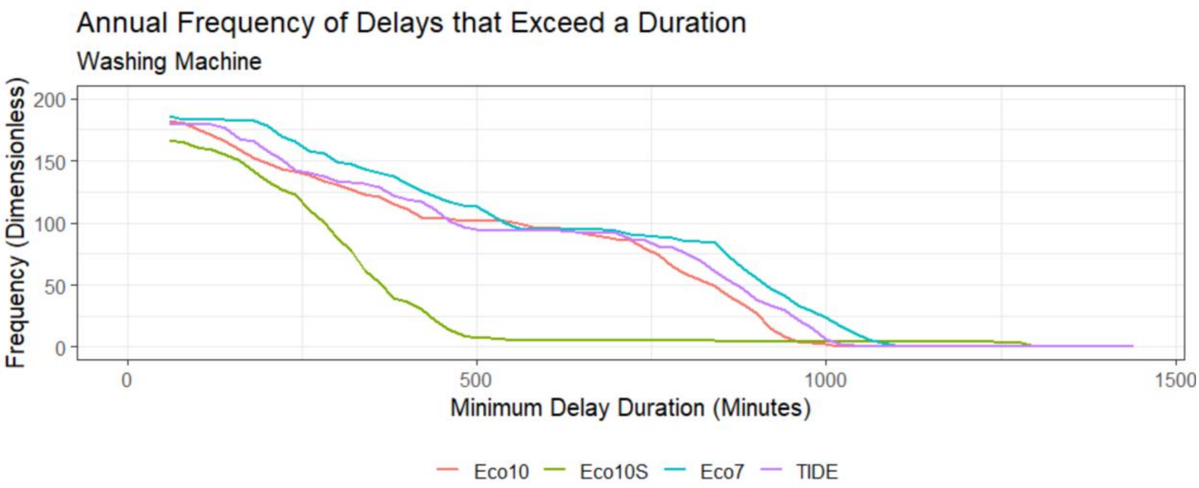

Figure 83 – DDP of Washing Machine

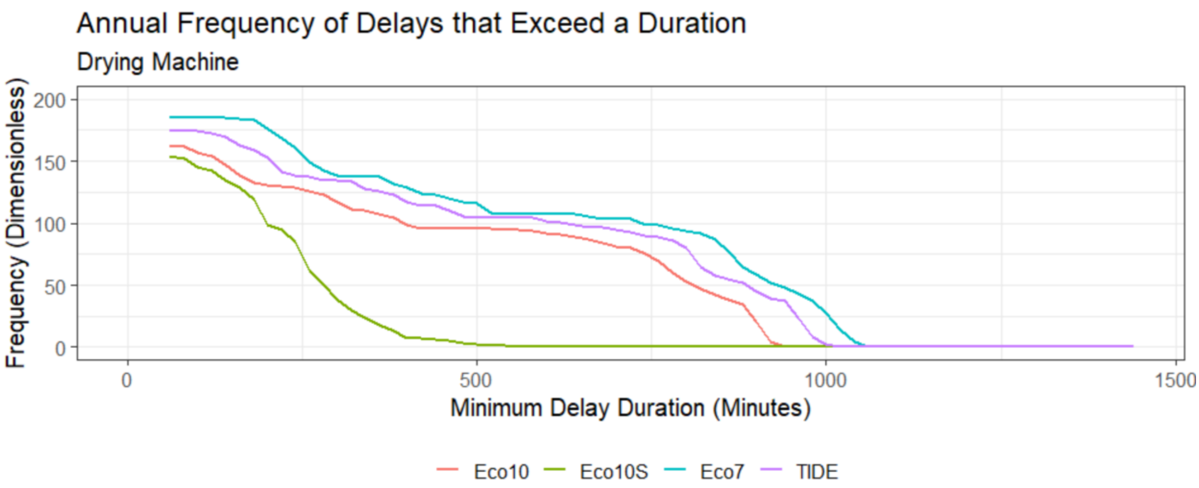

Figure 84 – DDP of Drying Machine

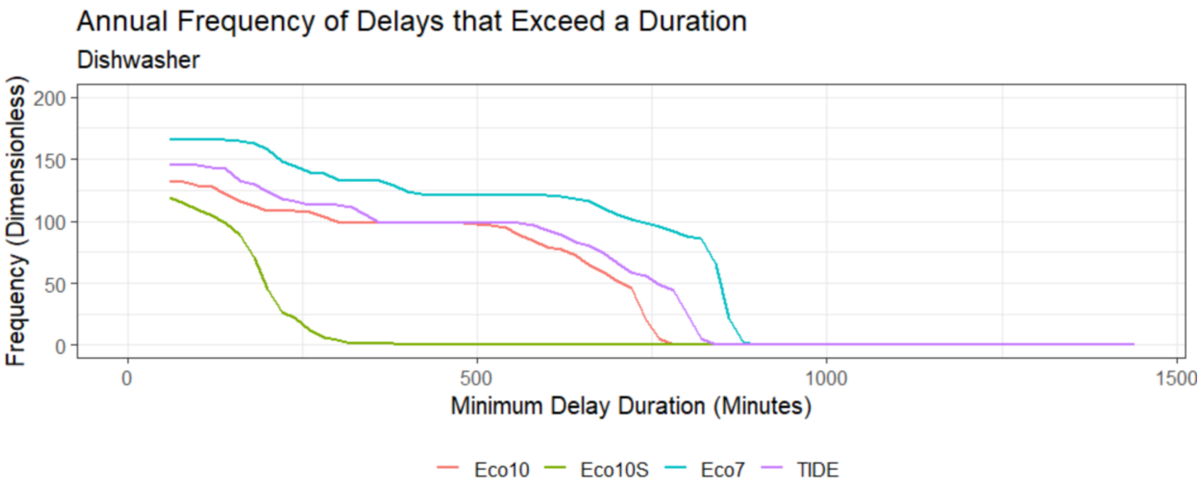

Figure 85 – DDP of Dishwasher

The plots of DDP share a common behaviour: downward linear (approximately) slope with occasional flattening. The steeper the slope between any two durations, the more the difference in frequency of occurrence, and thus, the more difference in convenience. Individual residents can be located on the x-axis based on their preferences on how much delay they can tolerate, then their convenience can be estimated as the frequency on the y-axis such that lower frequency is higher convenience. Two residents with different delay tolerance can estimate about the same 'convenience' where the DDP flattens; e.g. two residents with delay tolerance of 400 and 500 minutes for dishwasher (TIDE in Figure 85) measure about the same convenience. Also, a resident may opt for a different DR scenario to improve their 'convenience'; e.g. a resident with a delay tolerance of about 500 minutes for their Dishwasher can reduce the frequencies of 'inconvenience' by approximately 25 instances of delay (or 20%) in a year, by changing from Economy 7 to TIDE. At durations where the DDP of two DR scenarios coincide, the scenarios estimate the same level of convenience, and this means that a resident may not improve the convenience of using an appliance depending on their tolerance for delay. At a delay tolerance of about 620 minutes for Washing Machine, Figure 83 shows no preference for any of the DR scenarios, except for Economy 10S.

7.4.3 Delay Time Profile

Figure 86, Figure 87 and Figure 88 show the Delay Time Profile (DTP) of three appliances, each for the four DR scenarios. The DTP quantifies convenience as the inverse of the number of times a particular time of day falls during a delay in a year. Consequently, the x-axis represents the times of day. Taking the case of the Dishwasher, for instance in Figure 88, there is no delay observed at 6:00 am whereas there are about 100 instances of delays experienced (Economy 10 and TIDE) at 4:00 pm. Like the DDP plots, DR scenario with Economy 10S result in the least frequency of delays per time of day.

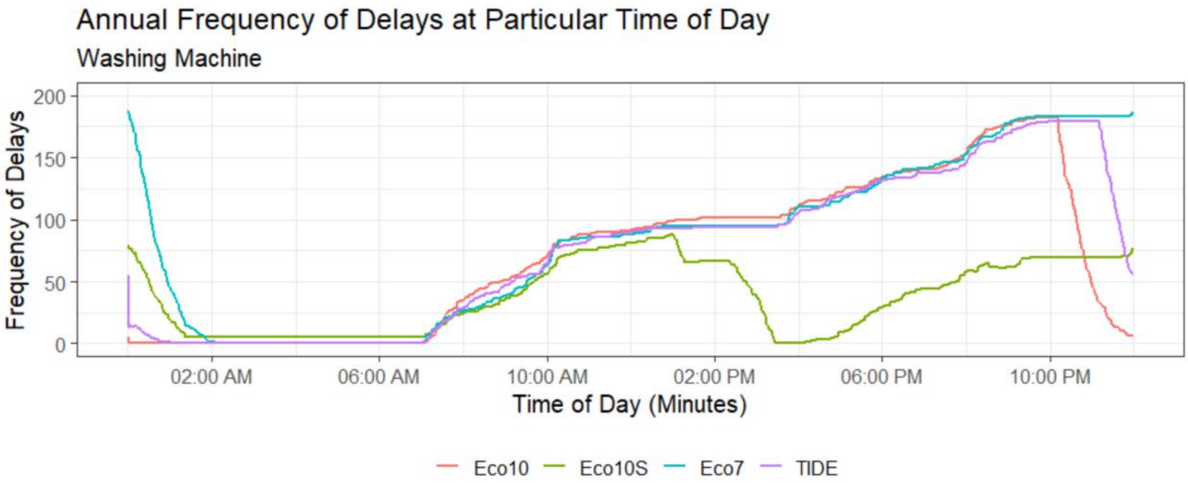

Figure 86 – DTP of Washing Machine

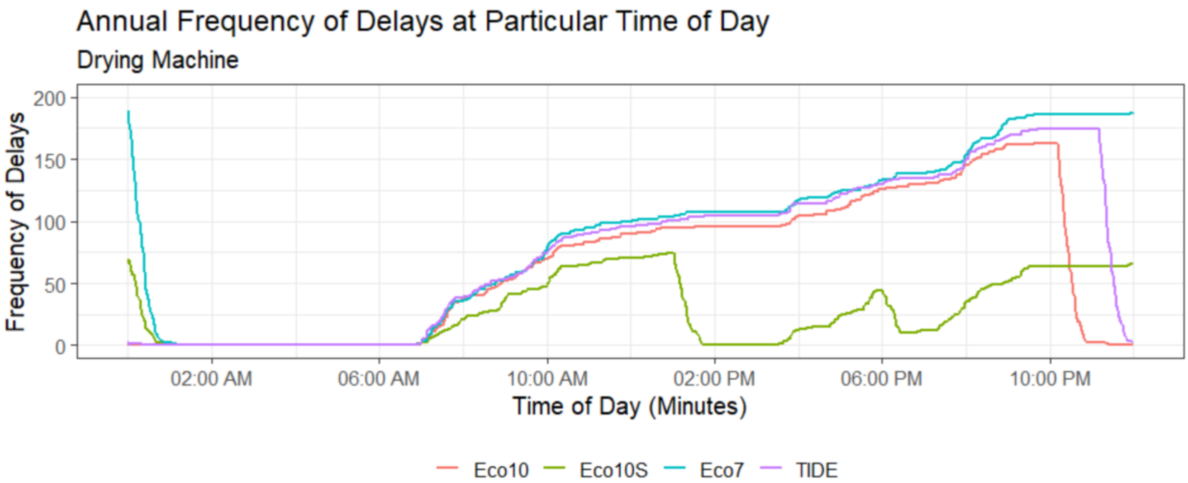

Figure 87 – DTP of Drying Machine

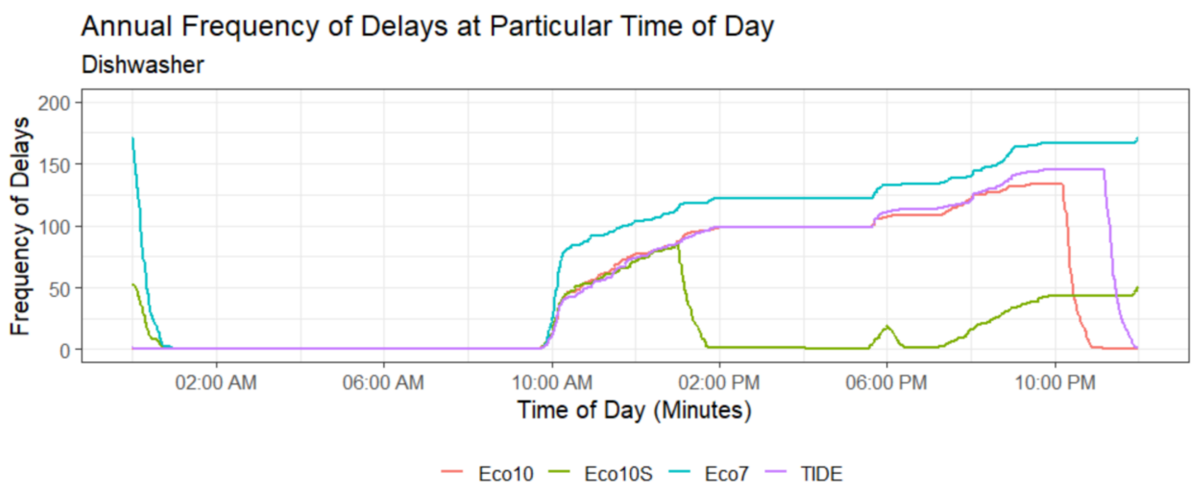

Figure 88 – DTP of Dishwasher

As expected, the DTP plots show no instances of delays during the daily periods where DR is active for each of the DR scenarios. Generally, the DTP of Economy 10S stands out from the other three. The instances of delay increase as the day progresses, remaining fixed (approximately) for significant periods in the day. The continuous increase follows the intuition that the closest time before DR is active is affected by all the delays since the last time DR was active. The flat periods represent times of equal convenience, for example, between 2:00 pm and 5:00 pm in Figure 88. DTP for Washing Machine and Drying Machine show little difference in convenience for most part of the day among the scenarios, but there is significant difference in the case of Dishwasher especially between Economy7 on the one hand and Economy 10 and TIDE on the other hand. Barring the different start of DR active hours, Economy 10 and TIDE have similar DTP for all the appliances. Looking at the Economy 10S, the DTP indicates lower delay – better convenience – for all appliances.

The plots stay flat at the same periods of the day across the DR scenarios, which indicates that there may be a common cause. The common cause is likely the random delay added before an appliance is turned on by the DR Agent, because the seed of the random generator is maintained across the DR scenarios which is generated daily, as mentioned earlier. However, this has not been confirmed during the study.

To estimate convenience, individual residents may have a specific time in the day where it is most inconvenient to have a delay. Such a resident may reduce their inconvenience from the Dishwasher at 2:00 pm, if the residence moves from Economy 7 to TIDE or Economy 10, by about 25 instances of delay (20%) in a year, or by 125 instances (100%) if the residence moves to Economy 10S. The assumption in all the applications of convenience plots (DDP and DTP) is that the resident is not flexible in their preference of 'convenience' for the duration of the simulation.

7.4.4 Plotting Convenience

The best performing DDPs and DTPs are in the same descending order: Economy 10S; Economy 10; TIDE; and Economy 7, which aligns with the mean and upper quantile delays in Figure 82. This also implies that the mean and upper quantile of the distributions may be sufficient to know which performs better. The results provide preliminary evidence that splitting the active DR hours leads to less delays and better DDP and DTP, which is better convenience. However, DDP and DTP are required to make decisions about specific preferences, and also to quantify the difference in performance of the scenarios.

Both DDP and DTP apply to an appliance in the specific residences from which it is plotted; that is the residence whose parameters are input to the simulation. Therefore, DDP or DTP cannot be applicable when any of the parameters of the residence changes (e.g. number of residents or addition/removal of an appliance in the residence), and they cannot be used to represent the same type of appliance in a different residence. However, comparing between two appliances in the same residence could be generalised for comparison between the same types of appliances in a different residence, assuming other variables in any residence remain proportionally the same. Furthermore, when a resident changes their habits (e.g. occupancy or frequency of use of appliance) which are parameters of the model, that would affect the applicability of the model because the underlying assumptions have changed.

The measurement of resident's convenience can be generalised beyond the model. The main requirement is to track two variables for every time an appliance is controlled by DR: time when an appliance would have operated in the absence of DR; time when the appliance operated during DR. Time includes the day and time of day. The variables necessitate that appliances are modelled in sufficient detail. Therefore, models that can keep track of these variables would be able to measure and visualise Convenience as DDP and DTP.

7.4.5 Daily Peak Demand

Figure 89 shows the boxplot of daily peak demand in the residence for a year in five scenarios which include the Baseline scenario where DR is not active, and the four scenarios where DR is active. Interestingly, the median peak is the same in all scenarios at 2507 W. But the Baseline scenario is consistently higher than all the other scenarios in terms of the first quantile, third quantile, mean and maximum. However, the difference among the DR scenarios is not explained by the number of active DR hours or whether the active DR hours are split or not. Moreover, this section compares the scenario with DR on the one hand, and the scenarios without DR on the other hand. The result shows that DR reduces the daily peak demand significantly in a residence. Utility companies are interested in aggregated peak demand from multiple residences, and how this DSM model could be used to address such problems is discussed in Chapter 8.

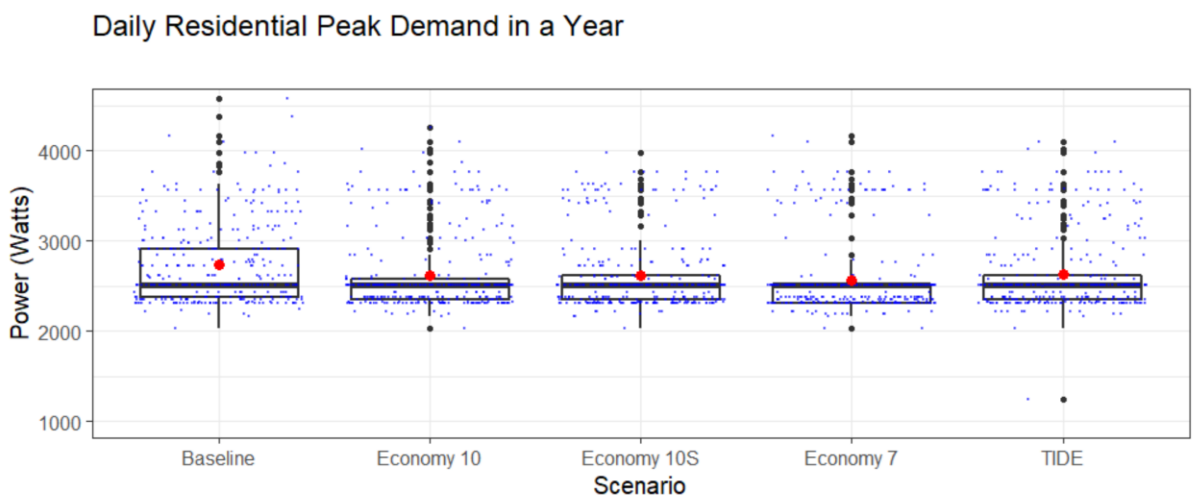

Figure 89 – Boxplot showing distribution of Daily Peak Demand in a residence in all scenarios

7.4.6 Money Saved

Table 31 shows the annual frequency of appliance use in all the scenarios and the cost per unit of energy (kWh) during operation. Given that the frequency of appliance use is almost the same across the scenarios, it can be safely assumed to be the same to ease estimation of cost savings per scenario. Since the energy consumption is the same in every cycle, the only changes to the operation of the appliances are time of operation and energy cost, but energy cost during DR is the cheapest for the ToU tariff. Therefore, the money saved from the operation of the three appliances in the different scenarios can be estimated in terms of the variable energy cost.

Scenario	Annual Frequency of Use			Energy Cost (p/kWh)	Tariff Name
	Washing Machine	Drying Machine	Dishwasher		
Baseline	205	205	204	21.6	

Economy 7	205	203	197	11.8	npower Standard SC
TIDE	205	203	198	4.9	TIDE
Economy 10	205	204	195	13.5	Ovo Energy Simpler Energy
Economy 10S	205	203	192	13.5	

Table 31 – Annual Frequency of appliances and energy unit cost for all scenarios

Given the assumptions above, there can be money saved or lost between scenarios only if the unit cost in energy is different. Table 32 shows a matrix to compare the percentage savings between any two scenarios, which in this study are any two tariffs. The table should be read as the savings when moving from column to row is x. For example, changing from Baseline to TIDE leads to a saving of 77%, whereas from TIDE to Economy 7 leads to a cost increase of 141%. Furthermore, any change to TIDE leads to savings because TIDE row is all positive, whereas all change to Baseline lead to cost increase because Baseline row is all negative. Therefore, the main determinant of savings when changing DR program is the unit cost of energy during DR (off-peak hours).

	Baseline	Economy 7	TIDE	Economy 10	Economy 10S
Baseline	0%	-83%	-341%	-60%	-60%
Economy 7	45%	0%	-141%	13%	13%
TIDE	77%	58%	0%	64%	64%
Economy 10	38%	-14%	-176%	0%	0%
Economy 10S	38%	-14%	-176%	0%	0%

Table 32 – Matrix of money savings and losses by changing tariff from column to row

7.5 Conclusion

This chapter addressed the sixth thesis objective, which is to demonstrate the application of the demand-side model from Chapter 6 in decision-making. Building on the demand-side SD model from Chapter 6, a DR subsystem was integrated. Four DR strategies were generated based on ToU tariffs, and three appliances were identified for the DR program. Each DR strategy was simulated as a DR scenario, and the scenarios were compared in terms of distribution of annual delay between appliance set-up and operation. The scenarios were also compared in terms of the following Performance Indicators: DDP, DTP, Daily Peak, and Money saved. Results from the scenarios were discussed. Therefore, it has been demonstrated that a bottom-up demand-side SD model can be utilised for decision-making analyses using Performance Indicators.

It was found that DR leads to monetary savings and reduction in daily peak demand. As to minimising the delay of the four DR scenarios, it was found that more hours of DR is better than less, earlier hours (relative to midnight) are better and splitting or distributing DR hours during the day is better than contiguous. The explanation that earlier DR hours lead to better sustainability performance needs to be explored further. Similar findings apply to DDP and DTP. Moreover, the importance of residents' preferences has been emphasised as capable of undermining the DR program. The use of a generic and binary DR Signal to represent the DR strategy allows for integration with many other algorithms for DR strategy that may have different objectives. The models created in this chapter and Chapter 6 can be combined, and this shall be discussed in the next chapter.

8 Combining Bottom-up SD Models

8.1 Introduction

So far, all the case-study chapters (Chapter 4 to Chapter 7) have either created models of RES or applied the models in analyses for decision-making. However, the models are yet to be combined with each other. The aim in this chapter is to combine smaller SD models into larger SD models. The two types of combination explored are integration and aggregation; but more attention is given to the former. Two levels of integration are explored in this study. The first level is at the residential-level where an RES model is expanded to include supply-side and demand-side, but remains an RES. The second level is at community-level where multiple RES are integrated to form an ICES.

On the residential-level of integration, two simulation models could be integrated if they have a common variable. The common variable may be in one of two cases: exogenous in one model and endogenous in the other; or endogenous in both. When the common variable is an exogenous variable in one model only, the output of one model (where the variable is endogenous) serves as an input to the other model (where the variable is exogenous). In that case, there is no need to run both models simultaneously because there is only one direction of influence. One model (where the variable is endogenous) can conclude running before using its output as input to the other model. On the other hand, when the common variable is endogenous in both models, both models must be run simultaneously because there is feedback between the models.

In this chapter, the integration between the supply-side RES model and demand-side RES model is of the type where the common variable is exogenous in the supply-side model while endogenous in the demand-side model. Two demand-side models will be integrated to a supply-side model separately, and the two resulting models will be compared. The demand-side models are CREST model and SD model, both of which were discussed in Chapter 6, while the supply-side model is the SD model from Chapter 4. The common variable is residential load, which is the output (endogenous) in the demand-side models, while an input (exogenous) to the supply-side SD model.

However, when the common variable in two simulation models is exogenous in both, the two models cannot really be integrated but can run in parallel instead and be aggregated because they do not affect each other. This is usually the case between multiple demand-side RES models, which may be aggregated to address EP problems with multiple residences, whereas integration is between multiple supply-side RES, or between supply-side and demand-side RES models.

On the community-level of integration, some of the options for integrating DER have been mentioned in Chapter 1 and these include Prosumer Community Groups (PCG) and Community Energy System (CES). Since ICES encompasses all the options mentioned, then PCG or CES can be ICES individually, and their combination is also an ICES. PCG is made up of prosumer residences that are able to exchange power, while CES is made up of consumer residences that share a common energy resource like storage. In this chapter, two types of ICES models are created: the first is a PCG, henceforth called PCG; the second is a combination of PCG and CES, henceforth called PCG-CES. Whereas residences in PCG have their individual batteries, the residences share a community battery instead in PCG-CES. In either case, each residence has a PV generation system. Each residential model is a SD supply-side model created in Chapter 4, but with different configuration. The methods section describes how the two models were created and compared. In other words, PCG is the ICES with residential batteries, while PCG-CES is the ICES with a community battery. The decision to deploy community batteries or residential batteries is an important problem in CEP, and it is discussed in Section 8.2.2. The two models are compared along technical, economic and environmental indicators.

This study explores the options of model integration by designing the case-study to compare the performance of community battery (PCG-CES) to equivalent capacity of residential batteries (PCG). Consequently, the literature review section focuses on community batteries because residential batteries and other aspects relevant to this chapter have been covered in previous chapters, especially Chapter 4 and Chapter 5. Furthermore, aggregation of DSM SD models of RES (from Chapter 7) will be discussed briefly to explore its use to answer EP problems with multiple residences in Section 8.5.

8.2 Literature Review

8.2.1 The trend towards DERs

Recently, the proliferation of PV systems has been increasing along with the capacity of installed Distributed Energy Resources (DERs) [344]. Battery Energy Storage (ES) systems are expected to complement the trend by improving the efficiency of energy use [344], [345].

It has been noted that the value of energy storage increases as the penetration of renewable energy technologies increase [346], [347].

Meanwhile, community Energy Storage (ES) is emerging as an alternative to the two common deployment of batteries, which is either distribution-grid connected or residential [348]; primarily serving the interests of the Distribution System Operator (DSO) or individual residences respectively. Community ES is able to serve both DSOs and individual residences [348], [349]. Moreover, the market is ready for business models that can support the deployment of Community ES [350].

8.2.2 Residential and community batteries

Community ES systems offer flexibility services to power networks within which they are embedded [351]. Increased self-consumption in a community system helps address the challenges of voltage rise, overcurrent and reverse power flows [345], [352]. Otherwise, the effects of these challenges may even reach customer equipment due to voltage control of distribution system [352]. Moreover, shared battery in an apartment building benefits both the consumers, by increasing self-consumption and self-sufficiency, and the power network (or DSO), by reducing peak demand [352].

Community ES may be compared with residential Energy Storage (ES) in terms of technical performance and economic cost. In terms of technical performance, it was found that batteries are more attractive in community ES than residential ES [349]. Since community demand profile is smoother than the individual homes, battery performance is enhanced [353], and consequently this reduces the power ratings of the batteries when averaged per household [348]. Substituting residential ES with community ES led to improved battery efficiency and reduced grid load [354]. Community ES has also been found to reach up to twice more effective than residential ES in reducing export from the community (to the Grid) [344], [345]. Furthermore, Grid congestion was found to be reduced using community ES [355]. A survey of studies showing the benefits of community ES over individual ES was carried out in [352], while another survey of studies showing the difference in energy consumption between community ES and individual ES was carried out in [352].

In terms of comparing financial cost, following from the reduction in energy imported per household, the cost of battery storage per household is reduced when battery is shared, as shown in the case of apartments [352]. In a larger community setting, levelised cost was reduced by more than a third in [353] and more than two-thirds in [348]. Moreover, it is expected that there will be reduction in capital cost by economies of scale on components of the storage system [356].

Despite the relative advantage of community ES over residential ES, some challenges persist especially economically. To address the challenge of high capital requirement of community ES [349], the use of community ES for multiple flexibility services has been demonstrated in [349], [351] and acknowledged in [357]. Moreover, flexibility services offer varying levels of benefit, for example (PV) time-shifting resulted in higher economic benefit than (demand) load-shifting in a CES [353]. Furthermore, the proliferation of Electric Vehicles (and hybrid), and their high-performance requirement from batteries, provides an opportunity for the use of second-life batteries in CES for grid flexibility services, as demonstrated in [358]. Given the increasing rate of residential ES deployment, and given that community ES is more effective, there is need for energy policy to facilitate deployment of community ES via market mechanisms [344].

8.2.3 Other Related Works

Many of the models in the literature include optimisation. Different optimisation objectives like energy minimisation, cost minimisation and self-sufficiency maximisation were considered in [359]. Furthermore, some optimisation models aimed for multiple objectives simultaneously. Demand load – via applying DSM on shiftable loads – and electricity prices were optimised in [351]. Similarly, [349] optimised demand load (by shifting load to cheaper tariffs) and PV energy (time-shifting). Some optimisation models considered the size of communities. Levelised cost was optimised for different community sizes by using the battery as variable demand (demand shifting) [348]. Furthermore, the optimum battery capacity per community size was sought in [348], [349]. Different community sizes were explored in the simulation to find sizes with the optimum performance [354].

Most of the communities in community ES literature are virtual; one exception being [355] which tested/experimented on a real-world CES. For example, using real load profiles and simulated solar generation profiles (from NREL's SAM), PV and battery (PV-BESS) was simulated (using more PV tools which models electricity flow and financial transactions) [352]. Then virtual buildings were created and grouped into communities [352]. In another example, virtual communities were created from data of real demand profile, real locations and synthetic (but realistic and based on real) PV profile [344]. Also, virtual communities of varying sizes were created from realistic (behaviour based) load profiles of residences and an adapted model of decentralised residences (SWARM 65) [354].

While providing ancillary services to support the wider grid operations, batteries in community ES carry out varying functions that may even be focused on maximising the utility of the customer without a clear benefit to the grid. Most community ES studies explore the use of batteries for time-shifting only e.g. [348], [352], [354]. However, multi-functional uses of batteries have also been explored. Energy arbitrage and peak-shaving were combined with the aim of economic benefit for an aggregator and a Distribution System Operator (DSO) [351], whereas time-shifting (of PV energy) and load-shifting (of demand) were combined in [349]. It had been demonstrated that time-shifting performs better than load-shifting [353]. Time-shifting requires a renewable source, and all the CES systems reviewed included PV.

Generally, in the case of optimisation models, the strategies for managing the batteries are the same as their objective functions/aims, and these have been discussed. In the case of simulation models, multiple approaches have been explored in managing community ES. Common strategies in multi-occupancy buildings were explored in [352] which includes: Evening Discharge; Charge Priority Evening Discharge; Single Cycle; Double Cycle; Peak Demand Threshold. Novel strategies were also proposed. Given the challenges of cumbersome communication infrastructure and lack of guarantee for the economic benefit of all members of a community, a two-stage (aggregated) control management and a pricing mechanism were demonstrated to address the challenges respectively in [360]. The control strategy is a combination of optimisation and rule-based control which minimises import from the grid, while the pricing mechanism is based on supply and demand ratio at the boundary of the community every 24 hours.

In general, community ES was compared with residential ES in [344], [349], [351]–[354]. For example, a scenario of Energy Arbitrage from the perspective of an aggregator was compared with an addition of peak-shaving which adds the perspective of a DSO [351]. Community ES with time-shifting was compared to community ES with load-shifting for three reference years in [353]. Furthermore, the combination of time-shifting and load-shifting were compared on the one hand, to a “zero carbon scenario” on the other hand in [349].

Whilst impact analyses was carried out for residential ES (as single homes) [361], [362], many impact analyses have been carried out for community ES. For example, techno-economic analysis in [352] [344], [348], [349], [351], [363]. Also, the impact of community ES on a distribution system was evaluated in [345]. Some of the technical indicators include: SCR [351], [352], [354], [360]; SSR [352], [354], [360]; number of incidents [351]; roundtrip efficiency [348]; annual discharge [348], equivalent full cycles [348], PV balance [354]; and demand balance [354]. Economic indicators include: annual revenue [351]; costs [351] Equivalent Annual Cost (EAC) [344]; EAV [344]; LCOE [351] also referred to levelised cost (LCOES) [348], [349]; LVOES [349]; PBP [351]; NPV [344], [352]; IRR [344], [349]; Participation Willingness Index [360]; and energy cost of community and individual residences [360].

8.3 Methodology

8.3.1 Case-Study Design

This study can be designed and described using the SA framework explained in Chapter 3, implemented in chapters 5 and 7, and illustrated in Figure 90 for the case-study in this chapter. The two steps to the design are: define the purpose of the study and identify required variables. Using the design, the next task is to build the simulation model and calculate the Performance Indicators. The case-study aims to compare the same capacity of residential batteries and community battery in terms of technical and environmental performance of the community as a whole, as well as the economic performance of individual residences. The technical Performance Indicators are SCR, SSR, Energy Loss Ratio (ELR), Total Import, Total Export, and Peak Import, while the environmental Performance Indicator is CO_2e Avoided (carbon dioxide equivalent avoided). The economic Performance Indicators are Net Internal Energy Bought and Net External Energy Bought which account for energy exchange within the community, and between the community and the Grid, respectively. The model and relevant variables, as well as calculation of indicators, are discussed in subsequent sections.

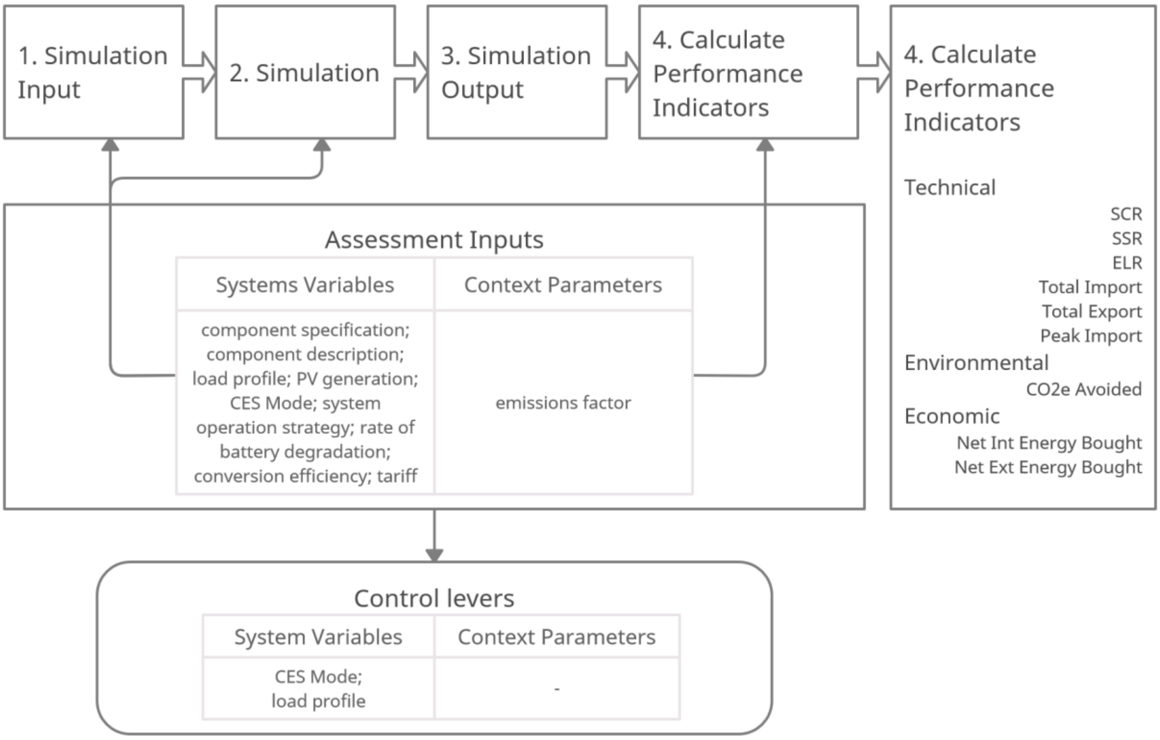

Figure 90 – Chapter 8 case-study design

8.3.2 Scenarios

To achieve the purpose of the case-study, the performance of two ICES models should be compared. The difference is that one uses residential batteries and is referred to as the PCG model, while the other uses a community battery and is referred to as the PCG-CES model. Each ICES is made up of six RES. Instead of creating two separate models, a composite model was created that contains both residential batteries and community battery but operates as either PCG or PCG-CES at any time, but not both. This is achieved via a switch variable CES Mode, which is also shown as a control lever in the study design: PCG when CES Mode = 0; or PCG-CES when CES Mode = 1. Therefore, the use of either ICES models can be treated as a scenario. In addition to CES Mode, the second variable that defines a scenario in the study design (Control Levers in Figure 90) is Load Profile. There are two options for the source of Load Demand: from CREST model, as it is in Chapter 4; or from the demand-side SD model (Chapter 6). The four resulting scenarios and associated Performance Indicators at the residential-level and community-level are shown in Table 33.

Scenario	Load Profile	CES Mode	Supply-side Model	Community-level Performance Indicator	Residential-level Performance Indicator
1a	CREST	1	PCG-CES	SCR SSR Energy Loss Ratio Total Import Total Export Peak Import CO_2e Avoided	Net Internal Energy Bought Net External Energy Bought
1b		0	PCG		
2a	SD Demand-side Model	1	PCG-CES		
2b		0	PCG		

Table 33 – Scenarios to be compared in this case study presented in terms of Control Levers and Performance Indicators

The focus of the scenario comparison is integration of SD models. There are two comparisons to be made. The first comparison is about integration of supply-side models at the community-level, while the second is about the integration of demand-side models at the residential-level. To achieve the first comparison scenarios 1a and 1b are compared on the one hand, then 2a and 2b are also compared. This is essentially a comparison between PCG and PCG-CES by keeping the Load Profile (demand-side model) the same. The second comparison is about the integration of supply-side SD model and demand-side SD model. Therefore, the comparison is between 1a and 2a on the one hand, and 1b and 2b on the other hand.

8.3.3 Subsystems, Integration and the Model

There are two types of subsystems that interact: a residential subsystem (Figure 91); and a community subsystem (Figure 92). The residential subsystem is based on the supply-side model from Chapter 4, whereas the community subsystem modifies the residential subsystem to enable P2P (Peer-to-Peer) energy transfer between the residential subsystems. Residence-level integration is achieved at the residential subsystem via Load Demand which is an exogenous variable. Being a supply-side model, the residential subsystem gets integrated with a demand-side model based on the shared variable Load Demand which is exogenous in the residential subsystem. On the other hand, community-level integration is achieved at the community subsystem via variables (From Residences) that are exogenous to the subsystem but endogenous to the residential subsystems, and also variables (To Residences) that are endogenous to the subsystem but exogenous to the residential subsystems. Since the created ICES model exhibits residence-level and community-level integration, all the scenarios are integrated at both levels.

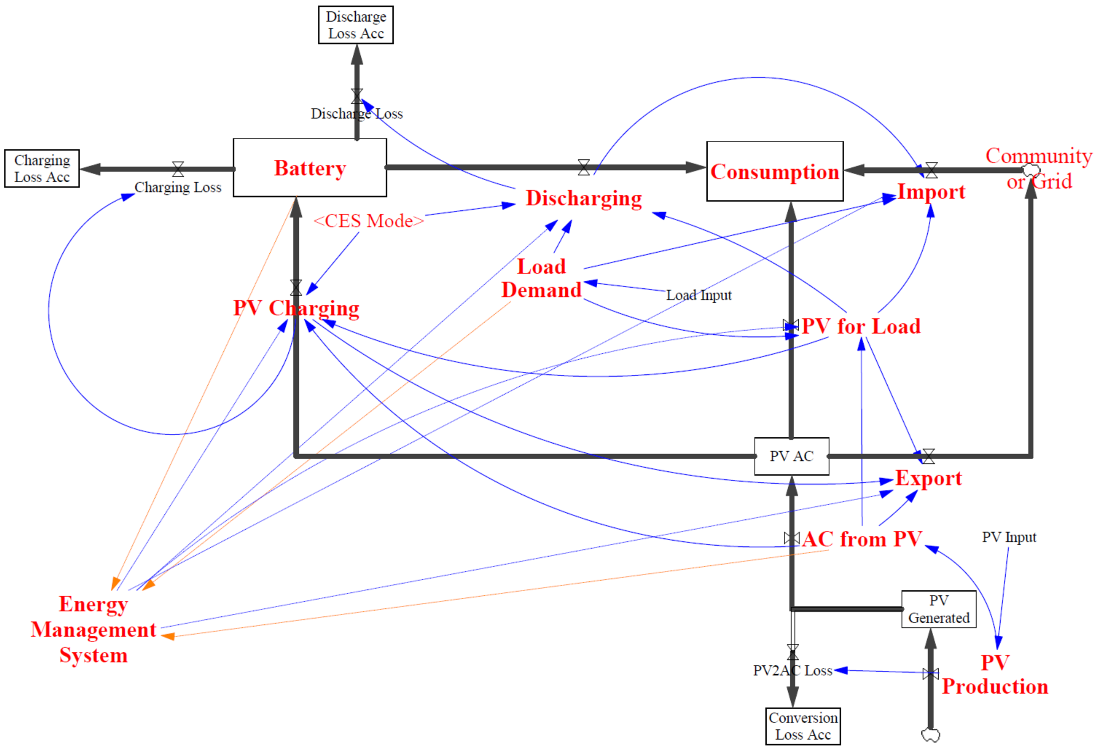

Figure 91 – Residential Subsystem

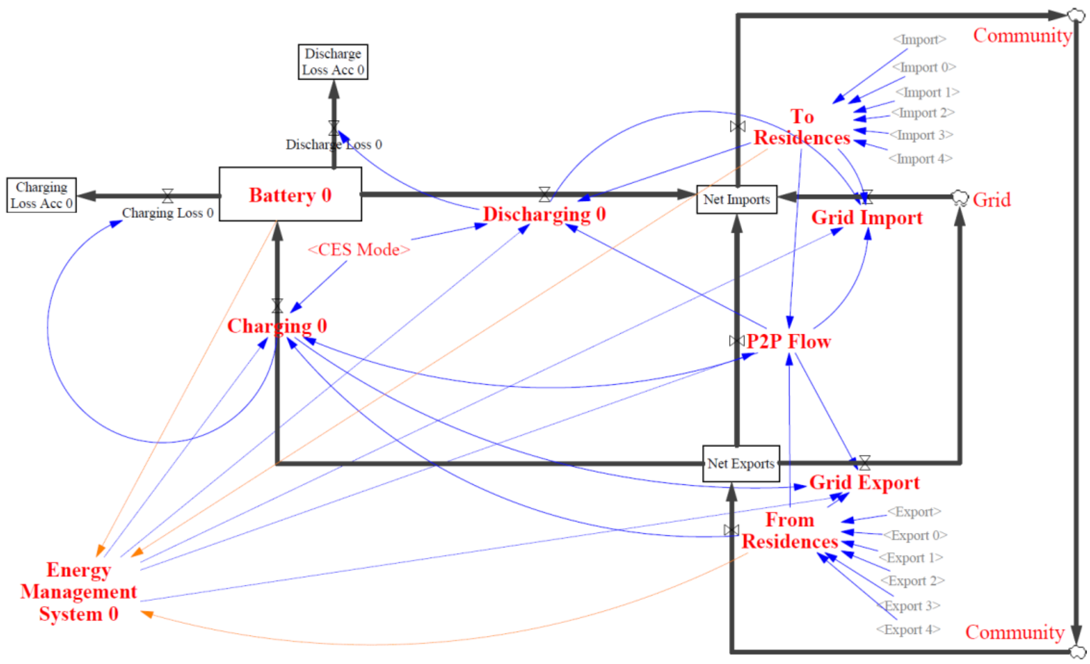

Figure 92 – Community subsystem

Based on the above, a simulation model of a community of six residences is presented. The model contains six residential subsystems integrated via one community subsystem. In the real world, this could represent houses with physical connection to a community hub, or an apartment building with six apartments that are physically connected. In the PCG model setup, the residences have individual batteries, whereas in the PCG-CES model setup, the residences share a battery which would be preferably located at the community hub. The infrastructure of the community hub may be provided by the DSO, owner of apartment building or jointly owned by the residences. The PV generation system is owned by the residences, so the ICES could be a partnership between any of the parties mentioned.

The aim of the Energy Management System (EMS) is to maximise self-consumption within the community. The management strategy is to export all excess generated PV power. In PCG, the residential batteries are charged first after the load of the residence is served, then excess power is exported, whereas in PCG-CES, excess power is exported after serving the load of the residence. Once exported from the residence, the priority is to serve other residences in the community with power deficit at the time, then what remains charges the community battery in PCG-CES, and what remains in the end is exported to the Grid in both models (PCG and PCG-CES). Therefore, the P2P (Peer-to-Peer) energy exchange between residences is managed at the community subsystem, and appears as a black box to the residential subsystems because the residences are not aware if their imports (and exports) are from (and to) the community or the Grid. Consequently, billing is also handled at the community subsystem.

The modelling process entails modification; therefore, it is similar to the process in Chapter 4, which created a model, then modified it. Therefore, this section focuses on the modifications to the already validated model in Chapter 4 and addresses only those validity tests relevant to the modification. All the changes to the model in Chapter 4 are reductive rather than additive when compared to the residential subsystem. The community subsystem is also derived from a modification of the residential subsystem, which is also mostly reductive with a single addition. Therefore, the following validity tests will be ignored in discussing the modification: Boundary Adequacy; Dimensional Consistency; Extreme Conditions. On the other hand, the following validity tests will be discussed: Structure Verification; Model Formulation; Parameter Calibration.

8.3.4 Modifications to Existing Models

8.3.4.1 Residential subsystem: Structure and Formulation

The change to the conceptual model from Chapter 4 is that there is no longer a material link from the grid to the battery and all associated links, because the battery may only be charged by the PV generator. This change is reflected in the simulation model. Furthermore, on the simulation model, the exogenous control signals are simply omitted from the formulation of the rule-based energy management. Therefore, the residential subsystem operates like the model in Chapter 4 that has a battery and PV but without signals to charge the battery overnight, and its imports and exports are handled by the community subsystem. Finally, the binary variable CES Mode has been introduced to allow for easy switching between the two effective models: residential batteries in PCG or community batteries in PCG-CES. Therefore, the conditions for charging and discharging variables depend on CES Mode; 'Charging' and 'Discharging' operate only when CES Mode is 0. When CES Mode is 1, then 'Charging 0' and 'Discharging 0' of the community subsystem operate.

8.3.4.2 Community subsystem: Structure and Formulation

The community subsystem is a modification of the residential subsystem. Names of components have been changed to reflect the change in scale accordingly: 'Export' to 'Grid Export'; 'Import' to 'Grid Import'; 'PV for Load' to 'P2P Flow'; 'AC from PV' to 'Net Export'; 'Consumption' to 'Net Imports'. The main changes to the conceptual model are two: the replacement of the PV source with excesses (exports) from residences; and addition of a flow to the residences from a stock 'Net Import'. Instant P2P energy transfer is achieved by the flow of energy from exports (From Residences) via 'PV for Load' to imports (To Residences). Excess energy that is not transferred instantly is used to charge the community battery, and what remains either due to rated power or full battery is exported to the Grid. Similarly, deficit energy of residences is first sought from the community battery before importing from the Grid. To achieve P2P energy exchange, nothing was changed in the EMS flowchart (from Chapter 4). Finally, the conditions for charging and discharging which depend on CES Mode are inverted compared to the residential subsystem so that when residential batteries are operational, community battery is disabled. In summary, the substantial changes from the residential subsystem are the removal of PV generation, facilitation of P2P energy flow, and inversion of conditions for CES Mode as appropriate for the PCG or PCG-CES models.

8.3.5 Parameters

The calibration of PV, inverters and batteries have been maintained from the model in Chapter 4 in each of the residential subsystems. The capacity of the community battery has been set to the aggregated capacity of the residential batteries in the community. Since the residential subsystems have the same battery capacity, the community battery is six times the capacity of each residence, and this provides a reasonable basis for comparing residential and community batteries. A cluster configuration of six residential battery inverters (product: SMA Sunny Island) can be made according to Multicluster-Box 6 which is a product by SMA. Whilst the rated power of a residential battery inverter is 3.3 kW, the clustered community inverter is 36 kW (according to the Multicluster-Box 6 manufacturer's sheet), which means the inverter for the community battery will be oversized for the six residences because summing the six is 19.8 kW (6 x 3.3), and that would lead to significant losses during conversion. The conversion efficiency curves of the residential and community battery inverters remain the same, after all, it is the same inverters and the efficiency curves are based on ratio of output or input to the rated power. Therefore, the choice of inefficiently sized inverter is a consequence of keeping the hardware the same across the compared scenarios. Table 34 summarises the parameter values.

Parameter	Residential Subsystem	Community Subsystem
Load Profile	From CREST Model or Demand-Side SD Model	-
PV Profile/Generation	From CERST Model	-
PV Capacity	2.08 kW	-
Battery Product	LG Chem RESU 6.4 EX	LG Chem RESU 6.4 EX x6
Battery Capacity	6.4 kWh	6x6.4 kWh
Battery Inverter Product	SMA Sunny Island	SMA Multicluster-Box 6
Battery Inverter Rated Power	3.3 kW	36 kW

Table 34 – Parameter of residential and community subsystems

Depending on the type of integration being demonstrated, the exogenous load profile may be sourced from different demand-side models. Since the residential subsystem is based on the supply-side model from Chapter 4 which sources its load profile from the CREST model, the CREST model is maintained when demonstrating integration at the community subsystem. However, when demonstrating integration at the residential subsystem, the demand-side SD model from Chapter 6 is used to generate the load profile. Regardless of the source, the load profile of the residences are generated for a different number of residents based on the UK 2020 data [341]. Since the percentage of houses with 1, 2, 3 and more than 4 persons are 28%, 35%, 16% and 21% respectively, two residences are assigned each with 1 and 2 residents, then

1 residence each with 3 and 4 residents. The number of residents is part of the input to the demand-side models that generates the appropriate load profile.

8.3.6 Proposed Tariff and Billing

A flat retail tariff is used between the community and the grid. Within the community, a simple tariff is proposed for P2P energy trade. The aim is that the internal buying price should not be higher than the buying price from the grid, and the internal selling price should not be lower than the selling price to the grid. The aim is similar to [360], though simplified, which is based on SDR and has been discussed in the Literature Review section. Whilst the approach in [360] is committed to economic theories of supply and demand, this paper is not; nor does this study explore the question of who benefits the most between consumers and prosumers.

The internal buying and selling prices are the same and it is set at the average of the Grid buying and selling price. In other words, the internal buying and selling price is midway between the Grid buying and selling prices. Payment is calculated towards a residence at the point of exporting from the residence which could be sent to other residences, charging the community battery or the Grid. Similarly, payment is calculated against a residence at the point of importing energy which could be from other residences, community battery or grid. Depending on the source or destination, the tariff differs: P2P and community battery are billed according to internal tariff, while the grid is billed according to the flat tariff on the grid.

Where multiple residences are simultaneously importing or exporting, the proportion of what is billed internally and externally is the same as the proportion of that residence to the total import or export from all the residences. The aim is to achieve a level of fairness by avoiding a situation where a residence gets all their energy internally (cheaper) while others get theirs from the grid (more expensive), even while the community import and export to the Grid remain the same. In other words, to each residence according to their demand, and from each apartment according to their supply. For example, in a given minute, a residence that demands an import of 10 W while all the other residences demand a total import of 40 W will be allocated 20% of the internal energy available, and 20% of energy imported from the grid (if the internal energy is not sufficient). Available energy is limited by rated power of inverters so having sufficient stored energy in the community battery does not mean it can be available at any given minute. A similar example applies to export. This billing approach is similar to [364] where the proportion allocated is based on the battery capacity of a residence, which eases central control, where the batteries are physically located at the residences but logically managed as a community storage.

The proposed internal tariff achieves the aim of offering a better price compared to the grid while considering fairness. The margin made from buying or selling internally rather than from or to the Grid is directly proportional to the difference between buying and selling prices on the Grid; buying price is at least equal to selling price. The larger the margin, the more income can be generated by members of the community. The proposed internal tariff is novel considering the literature reviewed, though it requires to be further explored for feasibility in practice.

8.3.7 Performance Indicators

The equations for the Performance Indicators are provided after a brief explanation and adapted to the variables in the SD simulation model. The community level indicators had been calculated in Chapter 5 but at residential level, therefore, their equations have to be modified to calculate at community level. CO_2e Avoided is also only meaningfully calculated at community level because all the internal energy is from a renewable source.

SCR (Self Consumption Rate) is the proportion of PV power produced which is used (see Eq. 8.4). SSR (Self Sufficiency Rate) is the proportion of the load demand which is served by power produced from the PV panels (see Eq. 8.5). ELR measures the amount of power generated by the PV but is lost in conversion while crossing the inverters (see Eq. 8.6*)*, which is modelled based on non-linear loss found in the specification sheet of the devices. CO_2e Avoided estimates the greenhouse gas (GHG) emissions avoided by generating power from renewable sources (PV), in mass (g) of CO_2e. To calculate CO_2e Avoided, the fraction of electricity sources that emit GHG is accounted for, as well as the emission factor used to convert electric energy into equivalent mass of CO_2 (see Eq. 8.7). In this paper, unlike most of the literature, energy losses are accounted for in the calculation of CO_2e Avoided.

With the residences as the billing units, Net Internal Energy Bought and Net External Energy Bought consider the internal and external tariffs respectively, then calculate the net amount of energy bought by a residence. The tariffs determine the proportion of a residence's sold or bought energy that comes from the community or from the Grid, as explained. To calculate the monetary value of the energy bought, the indicators which are in kWh can be multiplied by the internal or external tariff rate in £/kWh. The equations for Net Internal Energy Bought and Net

External Energy Bought are provided in Eq. 8.16 and Eq. 8.17 respectively. Description of the keys to the equations is provided in Table 35.

$$P_{PVDirectComm} = P_{P2P} + \sum_{i}^{r} P_{PVDirectRes} \qquad \text{Eq. 8.1}$$

$$P_{PVChargingTotal} = P_{PVChargingComm} + \sum_{i}^{r} P_{PVChargingRes} \qquad \text{Eq. 8.2}$$

$$P_{PVDischargingTotal} = P_{PVDischargingComm} + \sum_{i}^{r} P_{PVDischargingRes} \qquad \text{Eq. 8.3}$$

$$SCR = \frac{\sum_{t=1}^{n} \left(P_{PVDirectComm} + P_{PVChargingTotal}\right) \cdot \Delta t}{\sum_{t=1}^{n} P_{PVProduced} \cdot \Delta t} \qquad \text{Eq. 8.4}$$

$$SSR = \frac{\sum_{t=1}^{n} \left(P_{PVDirectComm} + P_{PVDischargingTotal}\right) \cdot \Delta t}{\sum_{t=1}^{n} P_{Demand} \cdot \Delta t} \qquad \text{Eq. 8.5}$$

$$ELR = \frac{\sum_{t=1}^{n} (P_{PV2AC} + P_{AC2Batt} + P_{Batt2AC}) \cdot \Delta t}{\sum_{t=1}^{n} P_{PVProduced} \cdot \Delta t} \qquad \text{Eq. 8.6}$$

$$CO2e\ Avoided = \sum_{t=1}^{n} \left(P_{PVDirect} + P_{PVDischarging} + P_{PVExport}\right) \times F_{CO2e} \times F_{GHGFuel} \cdot \Delta t \qquad \text{Eq. 8.7}$$

$$imRatio_i = \frac{imP_i}{imP_r} \qquad \text{Eq. 8.8}$$

$$P_{LocalImport} = P_{PVDischargingComm} + P_{P2P} \qquad \text{Eq. 8.9}$$

$$exRatio_i = \frac{exP_i}{exP_r} \qquad \text{Eq. 8.10}$$

$$P_{LocalExport} = P_{PVChargingComm} + P_{P2P} \qquad \text{Eq. 8.11}$$

$$boughtInternal_i = \sum_{t=1}^{n} \left(imRatio_i \times P_{LocalImport}\right) \cdot \Delta t \qquad \text{Eq. 8.12}$$

$$boughtExternal_i = \sum_{t=1}^{n} \left(imRatio_i \times P_{GridImport}\right) \cdot \Delta t \qquad \text{Eq. 8.13}$$

$$soldInternal_i = \sum_{t=1}^{n} \left(exRatio_i \times P_{LocalExport}\right) \cdot \Delta t$$ *Eq. 8.14*

$$soldExternal_i = \sum_{t=1}^{n} \left(exRatio_i \times P_{GridExport}\right) \cdot \Delta t$$ *Eq. 8.15*

$$Net\ Internal\ Bought = boughtInternal_i - soldInternal_i$$ *Eq. 8.16*

$$Net\ External\ Bought = boughtExternal_i - soldExternal_i$$ *Eq. 8.17*

Symbol	**Description**
i	Residence number.
r	Total number of residences in the community.
t	Simulation time-step.
n	Total simulation time-steps.
P_{P2P}	Excess power from all residences which goes to service other residential demands directly, at time *t*.
$P_{PVDirectRes}$	Power produced from PV at residences which goes to service residential demands directly, at time *t*.
$P_{PVDirectComm}$	Total power produced from PVs in the community which goes to service demands within the community directly, at time *t*.
$P_{PVChargingRes}$	Power produced from PV at residences which goes to charge the residential battery; this is zero when CES is on, at time *t*.
$P_{PVChargingComm}$	Portion of power produced from PV at residences which goes to charge the community battery; this is zero when CES is off, at time *t*.
$P_{PVChargingTotal}$	Total power produced from PV at residences which goes to charge the residential or community battery; when CES is off or on respectively, at time *t*.
$P_{PVProduced}$	Total power produced from all PV in the community, at time *t*.
$P_{PVDischargingRes}$	Power discharged from a residential battery for demand of the residence; this is zero when CES is on, at time *t*.
$P_{PVDischargingComm}$	Power discharged from the community battery for demand of residences in the community; this is zero when CES is off, at time *t*.
$P_{PVDischargingTotal}$	Total power discharged from batteries in the community for demand of residences, at time *t*.
P_{Demand}	Total demand of all the residences in the community, at time *t*.

P_{PV2AC}	Total non-linear power loss while converting from DC to AC for all community; PV generation from all residences, at time *t*.
$P_{AC2Batt}$	Total non-linear power loss converting from AC to DC for all community; mains to battery. When CES is on, this refers to the community battery only, and when CES is off, this refers to the total of all residential batteries, at time *t*.
$P_{Batt2AC}$	Total non-linear power loss converting from DC to AC for all community; battery to mains. When CES is on, this refers to the community battery only, and when CES is off, this refers to the total of all residential batteries, at time *t*.
$P_{GridImport}$	Total power imported from the grid to the community, at time t.
$P_{GridExport}$	Total power exported from the community to the grid, at time t.
imP_i	Power imported into residence *i* at time *t*.
imP_r	Total power imported into all *r* residences in the community at time *t*.
$imRatio_i$	Fraction of power imported to residence *i* in the total power imported to all residences in the community, at time *t*.
$P_{LocalImport}$	Total power imported from within the community (community battery and via P2P) into the residences, at time *t*.
exP_i	Power exported from residence *i* at time *t*.
exP_r	Total power exported from all *r* residences in the community at time *t*.
$exRatio_i$	Fraction of power exported from residence *i* in the total power exported from all residences in the community, at time *t*.
$P_{LocalExport}$	Total power exported to the community (community battery and via P2P) from the residences, at time *t*.
$boughtInternal_i$	Total power bought from within the community (community battery and via P2P) into residence *i* for all simulation time *t*.
$boughtExternal_i$	Total power bought from within the grid into residence *i* for all simulation time *t*.
$soldInternal_i$	Total power sold to the community (community battery and via P2P) from residence *i* for all simulation time *t*.
$soldExternal_i$	Total power sold to the grid from residence *i* for all simulation time *t*.

$Max_n\ (P_{Import})$	Maximum imported power from time t=0 to t=n.
$Max_n\ (P_{Export})$	Maximum exported power from time t=0 to t=n.
F_{CO2e}	Emissions factor for carbon dioxide.
$F_{GHGFuel}$	Fraction of fuels used for electricity generation which emit GHG.

Table 35 – Mathematical symbols

8.4 Results and Discussion

8.4.1 ICES: Integrating Supply-Side SD Models

Two comparisons will be made in this section. The first is between scenarios 1a and 1b, which have the CREST model as the source of the Load Profile. The second comparison is between 2a and 2b, which have the SD demand-side model from Chapter 6 as their source of Load Profile. Therefore, both comparisons will be between PCG and PCG-CES. However, while the first comparison will look into both community-level and residential-level, the second comparison will focus on the community level only.

8.4.1.1 Scenarios 1a and 1b: Community-level

Technically, having a community battery outperforms residential batteries in terms of SCR, SSR, Import and Export, but underperforms in terms of ELR and Peak Import. Table 36 shows the comparison of technical performance with green indicating better performance in the PCG-CES configuration relative to the PCG configuration, while red indicates worse performance. The improved performance in Import and SSR are negligible at a magnitude of 0.4% and 0.1% respectively, but PCG-CES does not export energy in the duration of a year which means all generated power has been stored and consumed within the community. Peak Import is higher in PCG-CES by 7.7% even though the total import is slightly lower. Most of the power generated from PV are consumed within the community because both models have high SCR, but PCG-CES performs better. More of the community demand is served by locally generated power in PCG-CES which has a 30% better performance in SSR. The lower value of SSR in PCG may be explained by limitation in storage (capacity or rated power) which is why PCG exports more while importing more at the same time. Environmentally, PCG-CES performs better than PCG by avoiding 24% more emissions.

Performance Indicator	**PCG Model**	**PCG-CES Model**	**Difference**

SCR	0.92	0.96	4.3%
SSR	*0.74*	*0.74*	*0.1%*
ELR	0.16	0.20	24.2%
Import (W)	392,305,953	390,750,523	-0.4%
Export (W)	55,612,690	-	-100.0%
Peak Import (W)	25,389	27,336	7.7%
CO_2e Avoided (g)	1,485,526	1,845,727	24.2%

Table 36 – Technical and environmental performance of the ICES models having load profile generated in CREST model

The worse performance of PCG-CES in ELR can be explained by the disproportionately high rated power for the cluster of six residential batteries. While each residential battery has a rated power of 3.3 kW, the cluster of six batteries and inverters set has a rated power of 36 kW, rather than a value closer to 3.3 kW multiplied by six. The same non-linear conversion efficiency was maintained for the individual inverters and the cluster because the same inverters are clustered, and the device datasheet does not override it. Since the same non-linear efficiency curve is used in the residence and community inverters, having a high rated power (oversized inverter) leads to high losses. Unfortunately, the minimum number of inverters that can be clustered are six, according to the device datasheet. Therefore, as the number of residences increase and match the size of the clustered inverters, less ELR should be observed. Finally, PCG-CES performs better environmentally by 24%.

The better technical performance of PCG-CES confirms other studies where community batteries performed better than residential batteries, which were discussed in Section 8.2.

8.4.1.2 Scenarios 1a and 1b: Residential-level

A summary of the billing comparison after a year is provided in Table 37 showing what was sold, bought, and the difference between the two. All the values are in kWh and so, to obtain the money equivalent, the value should be multiplied by the tariff rate which would be in £/kWh where £ is the currency; this allows flexibility for different tariff rates to be used. Consequently, the internal and external billing has been separated because their tariff rates would be different based on the proposed tariff in Section 8.3.6. Nonetheless, the comparison can be made about the two models without combining the internal and external bills.

Residence	Billing	Sold (kWh)		Bought (kWh)		Net Bought (kWh)	
		PCG	PCG-CES	PCG	PCG-CES	PCG	PCG-CES
Residence 1	Internal	45	2,500	4	1,143	-41	-1,357

Residence 2		42	2,531	2	1,222	-40	-1,310
Residence 3		11	2,123	22	1,773	12	-350
Residence 4		4	2,041	21	1,840	17	-201
Residence 5		1	1,804	64	2,388	63	584
Residence 6		24	2,403	12	1,414	-12	-989
Residence 1	External	322	-	651	1,131	329	1,131
Residence 2		305	-	675	1,123	369	1,123
Residence 3		62	-	1,075	928	1,013	928
Residence 4		40	-	1,171	917	1,132	917
Residence 5		12	-	2,109	1,227	2,097	1,227
Residence 6		185	-	857	1,188	672	1,188

Table 37 – Annual internal and external energy sold and bought from residences

Figure 93 visualises the comparison in Table 37, specifically on the internal billings of the two models. There are more internal transactions in the PCG-CES model, which is expected because there is a shared storage, whereas the only energy sold internally in PCG mode are excesses that cannot be stored in the residential storages (due to capacity or rated power), but once stored, the energy is used only by the host residence. On the other hand, in the PCG-CES model, energy that has been sold to the community battery would have to be bought if required, even by the same residence that sold it in the first place, which will lead to more internal transactions, though the economic cost to the residence will be negligible because the internal price of buying and selling is the same based on the proposed internal billing. However, (both residential and community) storage leads to losses from conversion, but direct P2P, where demand from one residence coincides with excess from another residence, does not incur losses from conversion. Finally, the Net Bought performs better across the residences in PCG-CES, because in all but Residence 5, the residences have been net-selling to the community as indicated by the negative values of Net Bought. When compared to external transactions carried out with the Grid, neither model appears to perform consistently better than the other across the residences, and this is shown in Figure 94.

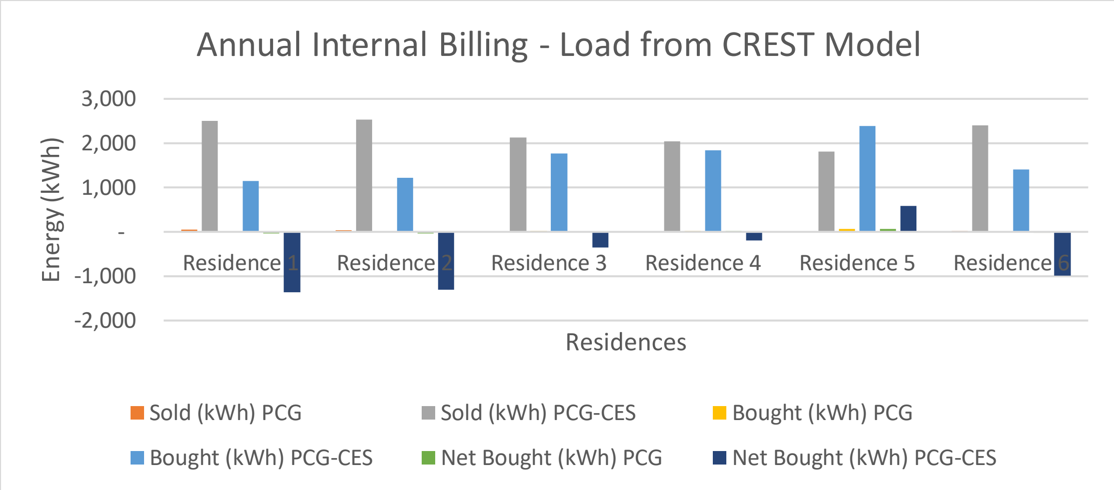

Figure 93 – Annual internal energy sold and bought from residences, in ICESs where load profile is generated by CREST model

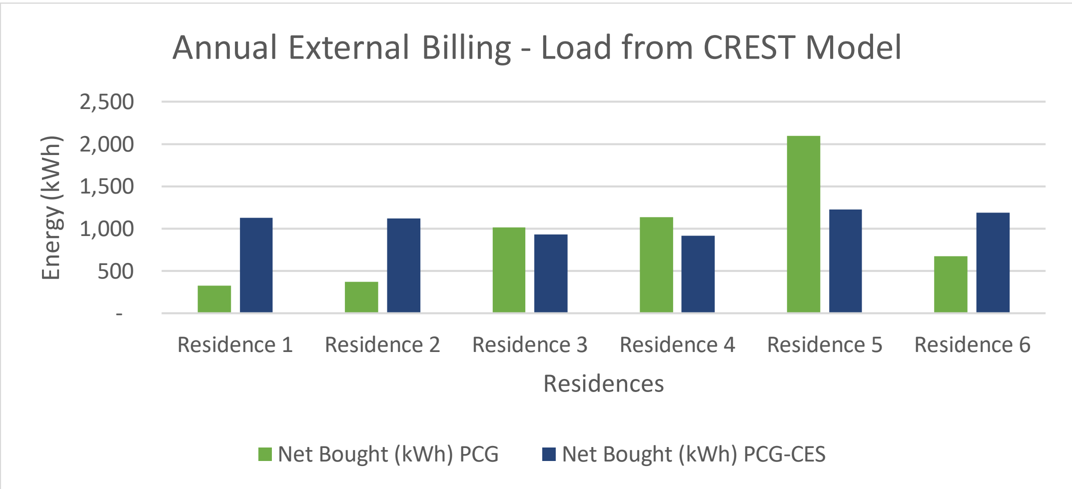

Figure 94 – Annual external energy sold and bought from residences, in ICESs where load profile is generated by CREST model

8.4.1.3 Scenarios 2a and 2b: Community-level

When Load Profile of the residences are replaced by the demand-side SD model, the outcome of community-level indicators are shown in Table 38. The differences between PCG and PCG-CES are negligible in terms of SSR, Peak Import and CO_2e Avoided, with difference of magnitude 0.1%, 0% and 1.1% respectively, based on Table 38. The largest difference is in ELR which doubles when using community battery, which is a worse performance. However, community batteries perform better in SCR, Import, and Export.

Performance Indicator	**PCG Model**	**PCG-CES Model**	**Difference**
SCR	0.46	0.62	34.4%

SSR	1.00	1.00	0.1%
ELR	0.15	0.31	104.0%
Import (W)	575,707	289,486	-49.7%
Export (W)	692,192,242	467,338,353	-32.5%
Peak Import (W)	3,477	3,477	0.0%
CO_2e Avoided (g)	1,493,148	1,477,188	-1.1%

Table 38 – Technical and environmental performance of the ICES models having load profile generated in SD model

8.4.2 ICES: Integrating Supply-Side and Demand-Side SD Models

This section compares 1a and 2a, as well as 1b and 2b, which is basically a comparison between CREST-load ICES and SD-load ICES, as applicable in PCG and PCG-CES. Whilst comparison between CREST and SD demand-side models of RES has been made in Chapter 6, the ICES models (PCG and PCG-CES) with load profile generated by the CREST model, and those generated by the SD model can be compared using Table 36 and Table 38 respectively. There are some similarities and differences with the indicators from the tables. The main similarities include improvement in SCR, Import and Export when using community battery instead of residential batteries, as well as community battery leading to more buying on net from the grid. The main differences include the following (both for PCG and PCG-CES), when residential load is generated from the demand-side SD model: SCR is lower; SSR is higher; Import is lower; Export is higher; and there is no significant difference between PCG and PCG-CES in CO_2e Avoided. The low values of SCR can be explained by the high values of Export because less is consumed in the community when much is exported out. The reason for the high difference between Import and Export could be explained by low temporal coincidence of demand and excess generation from different residences. When the excess precedes demand, it can be stored in the battery and exported, and Export should be high, but when demand precedes the excess, power is imported, and Import should be high. Since Export to the Grid is high while Import is low in the SD-load ICES (Table 38), it suggests that the excess power precedes the demand, whereas the opposite in the CREST-load ICES (Table 36) suggests that power demand precedes excess.

Whilst community battery improves internal community energy exchange (Figure 95), the lower coincidence (in SD based ICES) is further demonstrated in the external billing (Figure 96) which shows that all residences sell most of their excess generation to the grid. Residences in the ICES without community battery (PCG) can be seen to export more to the grid due to lack of coincident internal demand from residences in the community.

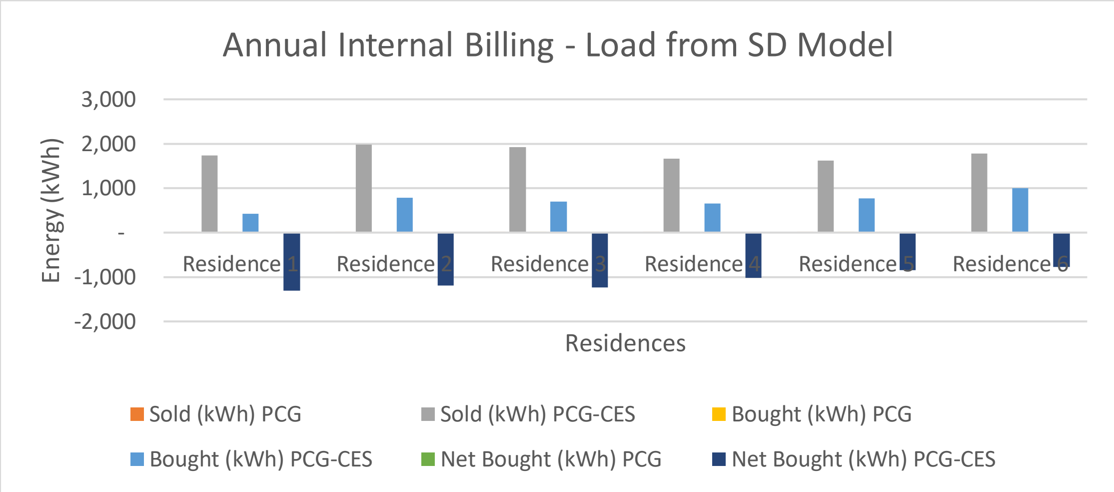

Figure 95 – Annual internal energy sold and bought from residences, in ICESs where load profile is generated by SD model

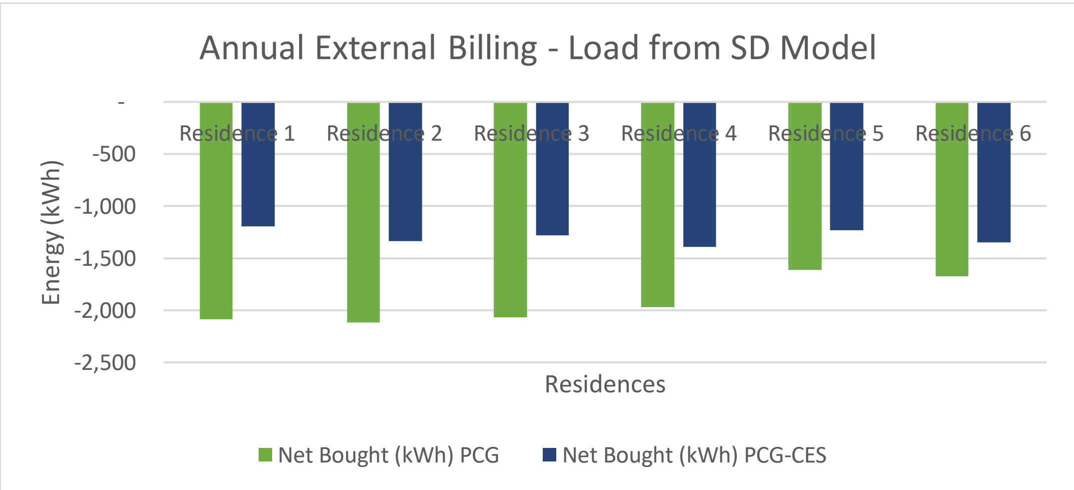

Figure 96 – Annual external energy sold and bought from residences, in ICESs where load profile is generated by SD model

Higher coincidence of residential demand and excesses can be achieved as the number of residences in the community increases. Another way to improve SCR for all the ICES models with residential batteries is to alter the operation strategy of the EMS such that demand from another residence in the community may be served by a residential battery from another residence; technically, this would make the ICES a Virtual Power Plant (VPP) instead of PCG. As for the ICES with community battery, SCR may be improved by increasing the capacity of the battery because the high export is due to charging the capacity of the battery. Second-life batteries could also be used as a cheaper option to store large amounts of energy which will be utilised within a short time. Having second life batteries would be the equivalent of expanding the window of coincidence such that excess energy can serve demand from other residences within the short time e.g. 2 hours.

8.4.3 Aggregating Demand-Side Residence Models for CEP

Since ICES is defined in terms of the supply-side technologies it integrates, only supply-side models can combine to form an ICES, as discussed thus far. However, demand-side models can be integrated to the supply-side models as demonstrated, but can also be combined to deal with other demand-side models to deal with problems involving groups of RES. For example, utility companies that are interested in aggregated peak demand from multiple residences, and possibly how to influence these demands to make the most efficient use of their existing infrastructure. Two demand-side models of SD have been created: a residential appliance load generation model in Chapter 6 and a residential DSM model in Chapter 7. Both can be aggregated to address problems of groups of residences, and may need to be integrated only if demands of residences affect each other.

There are two ways to aggregate demand-side models, at least: brute-force aggregation and statistical aggregation. Brute-force is similar to the integration of multiple residential subsystems via a community subsystem. However, this would be tedious because of detailed and dynamic complexity (Section **Error! Reference source not found.**), where every appliance in every residence, as well as every resident, must be set with parameters, while there is interdependency among appliances and residents in each residence.

On the other hand, a statistical aggregation could estimate the demand of multiple residences based on a single or few residences. A simple but unrealistic example is simply to multiply the demand of a single residence by the number of residences in the group. Another example would be to simulate a few residences of different types, which could be based on number of residents or resident type, then multiply the residences according to the proportion of the population they represent. In another example, inference about multiple similar residences can be made assuming their peak loads occur within a predictable period of day, assuming they are not uniformly spread during the day across multiple residences. Therefore, the daily peaks from multiple instances of the simulation (of a single residence) can be randomly distributed over the periods of day (e.g. four-hour slices), and then summed per minute to determine a peak of the multiple residences. The statistical approach is less demanding but could be reasonably representative. Comparing brute-force and statistical combinations can be explored in further work.

8.5 Conclusion

This chapter addressed the seventh thesis objective, which is to combine the supply-side and demand-side models and to demonstrate decision-making at community-level. Whilst the previous case-study chapters can be stand-alone and make unique contributions especially at the residential level, this chapter demonstrated how they can be utilised in CEP. The supply-side models were integrated with demand-side models, with the latter as exogenous variables to the former. Furthermore, the supply-side models (residential subsystems) were integrated with each other via a community subsystem, and an ICES was created. Furthermore, the aggregation of demand-side RES models for CEP problems were discussed. The integration of SD models from previous chapters was explored by way of a case-study. In the case-study, two forms of ICES models (PCG and PCG-CES) were created and compared to find out whether community battery or residential batteries perform better for the community (technically and environmentally) and residences (economically).

This case-study confirms the findings from previous studies in the literature where community battery performed better than equivalent capacity of residential batteries in terms of technical indicators SCR, SSR, Total Import, and Total Export at the community-level. The exception in the case-study was Peak Import which was argued to be negligible. Previous studies did not consider ELR as a technical indicator but it was found that community battery performs worse in terms of ELR which can be attributed to having oversized inverters as a result of clustering residential batteries. The difference in environmental indicator (CO_2e Avoided) is also negligible.

On the residential level, the different residences performed consistently in terms of internal energy exchange within the community, having more exchange with community battery than with residential batteries. Cumulatively, having a community battery resulted in more energy bought from the grid than with residential batteries. However, when the load profile is generated by the SD demand-side model from Chapter 6, residences sell to the grid on net (over a year), compared to buying on net when load profile is generated from the CREST model. The reason for this could be due to the coincidence of excess PV generation and demand from residences, given the energy management strategy.

The next chapter will conclude the thesis.

9 Conclusion

9.1 Introduction

The conclusion chapter has five sections: Overview; Answering Research Questions; Novel Contributions; Reflections; and Opportunities for Future Research. The Overview section will summarise the main storyline of the thesis, guided by the research aims and objectives. Therefore, the Overview section will be sequential, in the order of the chapters. On the other hand, the Reflections section will be thematic, and not necessarily sequential, by focusing on strengths, limitations and insights that are important, but may not be relevant to the main thesis storyline. Next, the thesis research questions will be addressed. Finally, opportunities for future research will be explored.

9.2 Overview

Chapter 1 began with the research motivation and introduced SD as a path to realise the motivation, then presented the research question, strategy, aims, and objectives. The summary of contributions of the thesis research was also presented, and the chapter was concluded with the structure of the thesis. The research motivation began by highlighting the importance of energy for HDI, EP and the modelling of energy systems when making decision on energy problems. After identifying some challenges of CEP, SD was identified as a versatile methodology that could address the challenges. Therefore, the research motivation was to demonstrate that SD could be a comprehensive CEP methodology.

SD was introduced as one of the many systems methodologies but with unique versatility in the types of problems it can handle. Thereafter, the research question, strategy, aims, objectives and summary of contributions were presented. The research strategy was based on the systems concept of hierarchy of systems, and bottom-up simulation, which was to work on case-studies by modelling RES while carrying out analyses used in CEP for decision-making, then at the final case-study, combine the multiple RES into an ICES and carry out analyses expected in CEP. Chapter 1 was concluded with a structure of the thesis, which discussed the content of the chapters and the flow of the thesis in terms of how later chapters build on earlier chapters.

Chapter 2 reviewed the literature of SA and CEP with a focus on process and methodology. After clarifying the concept of SA, the measurements of SA were shown to result from understandings of sustainability. SA process, methods, tools and issues were also reviewed. Next, the CEP methodology was explained as phases, and the corresponding groups of methods were reviewed, while keeping SD in perspective. Eventually, CEP was argued to incorporate SA if CEP evaluates scenarios or configurations of models using performance indicators from the pillars of sustainability; instances where SA was used for EP at community-level were also cited. Having identified demonstrations of SD in the CEP process, a SD-centred CEP methodology was proposed that would maximise the comprehensiveness of SD; which is the motivation of the research. Thereafter, the gaps in demonstration of SD in the proposed methodology were identified to be bottom-up simulations, which would be demonstrated in the case-study chapters (chapters 4-8).

Prior to the case-studies, the shared methodology of the case-study chapters was presented in Chapter 3. The shared methodology includes the SD modelling process and a proposed framework for SA. The SD modelling process included the validity tests and the modelling languages of CLD and SFD. The SA framework is descriptive, and could be used to design a prospective or existing studies. The SA framework utilises a generic simulation modelling process, but the SD modelling process was used in the case-study chapters. Depending on the aim of a case-study chapter, the SD modelling process or the SA framework were utilised, or both.

Each case-study chapter (chapters 4-8) contains a literature review and methodology sections, before discussing results. The literature review sections focused on the most relevant literature to the aim of the case-study, while the methodology sections focused on how the aim was pursued. Chapter 4 and Chapter 5 dealt with supply-side models, Chapter 6 and Chapter 7 dealt with demand-side models, then Chapter 8 dealt with combining the models from chapters 4-7. On the supply-side, Chapter 4 demonstrated a valid supply-side SD model of a RES using a bottom-up approach. Building on that, Chapter 5 carried out impact analyses using the SA framework, as would be expected in EP for decision-making. The impacts were assessed using Performance Indicators from the sustainability pillars, which include SCR, SSR, ELR, NPV, PBP and CO_2e Avoided. On the demand-side, synthetic residential appliance load was generated in Chapter 6 using SD from the bottom-up, and the result was found to be realistic. Chapter 7 integrated a DSM subsystem to the model from Chapter 6, which enabled the evaluation of DSM strategies for decision-making based on performance/sustainability indicators, which include Daily Peak Demand, Money Saved, Delay, DDP and DTP.

Finally, Chapter 8 integrated supply-side SD models with demand-side SD models, as well as multiple supply-side SD models. Aggregation of multiple demand-side models was also discussed briefly for community load generation and for community DSM. Since the integration of multiple SD supply-side RES models results in ICES, the integration of the models was explored by way of a case-study that compared ICES. Two ICES options were considered: PCG and CES. PCG utilised residential batteries whereas CES utilised shared community batteries. The two forms of ICES were compared using Performance Indicators at the community-level and residential-level. At the community-level, indicators include SCR, SSR, ELR, Total Import, Total Export, Peak Import, and CO_2e Avoided, whereas at the residential-level, indicators include Net Internal Energy Bought and Net External Energy Bought. The comparison of ICES (residential and community batteries) was first carried out using supply-side RES with load generated by the CREST model. Then the comparison was repeated with residential load generated by the SD model from Chapter 6. In addition to comparing between the ICES, the results of the comparison were also compared between the CREST-load ICES and the SD-load ICES. Nonetheless, both were demonstrated in use for decision-making in EP.

9.3 Answering the Research Question

The thesis research question is: Is System Dynamics effective as a comprehensive methodology for sustainable Community Energy Planning?

The research question could be answered in the affirmative in four steps. First, is to show that SD can be a comprehensive methodology for CEP. Since to be effective is to be valid and useful (see Section 1.4), the second step is to show that the SD models generated as part of the comprehensive methodology are valid, while the third step is to show that the SD models are demonstrated in decision-making analysis. The fourth step is to show that the decision-making analysis assesses sustainability impact.

First, on SD being a comprehensive methodology for CEP − Given the methods in the CEP methodology (Section 2.4.2), SD alone cannot be a comprehensive methodology for CEP. Hence the proposed CEP methodology (Section 2.6) includes more than SD as a method. However, comprehensiveness of SD as a methodology for CEP can be understood in terms of two components: sufficiency of SD across CEP phase; and integration of CEP phases by SD. Given the reviewed literature and the presented case-studies, SD has been found to be sufficient for Phase I but only partially sufficient for Phase II and Phase III. The second component of comprehensiveness is the integrating role SD plays in the CEP methodology between the phases by being present in all the phases, while having a common unifying language. Being a common language in the phases promotes transparency, and facilitates communication among participants, and thereby supports participatory and multi-disciplinary approaches. There are three possible integration points – between Phase I and II, between Phase I and III, between Phase II and III – and SD integrates in the first two based on the reviewed literature. Therefore, SD is significantly comprehensive within the CEP methodology.

Regarding the second step on the validity of the SD models, the models that can be generated by the proposed CEP methodology can be divided into models demonstrated prior to this research, and models created in this research (which are bottom-up SD models). All the SD models cited in Chapter 2 as demonstrations of the proposed methodology, while identifying aspects of the methodology that have not been demonstrated, are valid. On the other hand, all the models created in the case-studies were subjected to validity tests and demonstrated to be valid, up to the point of Behaviour Reproduction (validity was discussed in Section 3.2.2). Behaviour reproduction validity tests were carried out for the two base models (Chapter 4 and Chapter 6), which were utilised in decision-making analyses (Chapter 5, Chapter 7 and Chapter 8). Where the models were modified in terms of the parameters (Chapter 5) or additional subsystem (Chapter 7 and Chapter 8), the modifications were justified by addressing the concerns of the validity tests.

Third, on demonstration of the SD models in decision-making analyses − Where the models were applied in decision-making analyses (Chapter 5, Chapter 7 and Chapter 8), the main form of analysis was scenario analysis. Decision-making in scenario analysis is simply to select some scenarios over others based on the analyses and the decision-maker’s preferences. Realistic scenarios were compared, and decisions can be made based on the performance of the scenarios. Some of the scenarios are defined by the presence or absence of system components (endogenous variables in Chapter 7 and Chapter 8), or values of system parameters (exogenous variables in Chapter 5 and Chapter 7). Scenario analysis was also used to compare the effects of modelling some features of the system like non-linear conversion efficiency (Chapter 4, Chapter 5) and battery degradation (Chapter 5), which could be used for decision-making on the modelling methodology.

Related to the third step, the fourth step focuses on the types of indicators used to assess the performance of the scenarios. All indicators were classified under the pillars of sustainability: technical; economic; environmental. Some examples of indicators include: SCR, SSR, ELR, Daily Peak Power, Total Import, Total Export, Peak Import for technical (Chapter 5, Chapter 7, Chapter 8); NPV, PBP, Money Saved, Net Internal Energy Bought, Net External Energy Bought for economic (Chapter 5, Chapter 7, Chapter 8); and CO_2e Avoided for environmental (Chapter 5). In addition to the three pillars, cultural indicators were explored as DDP, DTP (Chapter 7), and culture may be considered a pillar of sustainability if it is understood that poor cultural alignment between users and a technology could undermine the technology.

Having discussed the four steps above, the thesis research question has been answered in the affirmative, with the following conditions: SD alone cannot be fully comprehensive for the CEP methodology, but SD can be highly comprehensive in terms of applicability in the phases and integrating the phases. Therefore, System Dynamics can be effective as a comprehensive methodology for sustainable Community Energy Planning.

9.4 Novel Contribution

The novel contributions in this work can be categorised into three. The first is the main contribution which connects the thesis aims and objectives, following a thread through the different chapters, and culminating in the fulfilment of the thesis objectives. These main contributions follow the main thesis storyline, guided by the thesis objectives, and were therefore planned from the beginning of the thesis research project. The second category of contributions are within the case-study chapters (chapters 4-8) only, that were not planned at the beginning but were pursued either because of an identified gap in the specific literature of the case-study, or inadvertently discovered as an opportunity worth pursuing. The third category are within the introductory chapters (chapters 1-3), but do not qualify to be in the first category because they do not fulfil any thesis objective directly. Table 39 shows the categorisation of contributions and the chapters the contributions can be found. The first category is named Converging Storyline, the second is Divergent Case-study, and the third is Divergent Introductory.

Contribution Category	Converging Storyline	Divergent Case-study	Divergent Introductory
Chapters	2, 4, 5, 6, 7, 8	4, 5, 6, 7, 8	2, 3

Table 39 – Categorisation of novel contributions and the chapters containing the contributions

The main contribution (Converging Storyline) of the case-studies has been the proposal of a SD-centred methodology for CEP, and the demonstration of valid SD models of energy systems from the bottom-up. Furthermore, the application of these models was demonstrated by evaluating scenarios and configurations of systems for decision-making using indicators along the pillars of sustainability. The models have been created at residential-level as well as community-level. Based on Table 39, the literature review chapter (Chapter 2) and every case-study chapter (chapters 4-8) contains a contribution to the thesis objectives. Chapter 2 proposes a SD-centred CEP methodology that takes advantage of the versatility of SD. Chapter 4 represents the first attempt at a valid supply-side SD model from the bottom-up. Chapter 5 represents the first attempt at using a bottom-up supply-side SD model in decision-making analyses. Chapter 6 represents the first attempt at a valid demand-side SD model from the bottom-up. Chapter 7 represents the first attempt at DSM SD model from the bottom-up, as well as using a demand-side model in decision-making analysis. SD had been used to design DSM pricing using a top-down approach in [365], but there has been no SD model for DSM using a bottom-up approach. Finally, Chapter 8 represents the first attempt in integrating bottom-up SD models (supply-side and demand-side) into a larger SD model, then used for decision-making analyses. The significance of these contributions is that they fulfil the thesis objectives.

In the second category of contributions (Divergent Case-study), the first contribution is modelling non-linear efficiency of inverters (for PV and battery). It was surprising to find that this well-known property had not been modelled in the surveyed literature on bottom-up simulation models (supply-side). Past studies assume a constant value for conversion efficiency, perhaps because they assume that the effect of a fluctuating conversion efficiency is insignificant. However, the effect of modelling non-linear efficiency was compared with constant conversion efficiency in Chapter 4 and Chapter 5, and the effect was found to be significant in both cases. This has implication on decision-making about inverter size, and the choice to model non-linear efficiency or not.

Another set of contributions are novel indicators for evaluating the performance of a system, which include Energy Loss Ratio (ELR), Delay Duration Profile (DDP) and Delay Time Profile

(DTP). ELR was introduced in Chapter 5, then also used in Chapter 8. Following from non-linear efficiency, ELR is a technical indicator that measures how much of the generated energy is lost before use, focusing on losses from conversion at inverters. With a constant energy conversion efficiency, as is prevalent in previous studies, this indicator is simple to calculate by multiplying the total energy generated by the constant conversion efficiency. However, with non-linear efficiency, the ratio of power generated to the rated power of the inverter determines the energy loss per time, in the case of the PV inverter, and the ratios of charging power to rated power and load demand to rated power in the case of battery inverter. ELR, as a contribution, is also of significant when making decisions about inverter size.

DDP and DTP are to be used for making decisions about convenience of DSM/DR strategies on appliance-use at residential-level. Unlike other indicators that are calculated as constant values, DDP and DTP are first generated as functions of variables that represent the preferences of residents, and therefore they require additional input from the decision-maker to resolve to a value. DDP is a function of maximum tolerable delay from the appliance, while DTP is a function of time-range of day where delay from appliance use cannot be tolerated. DDP and DTP were explored in Chapter 7. Whilst all the other indicators can be utilised at residential-level and community-level, DDP and DTP can be used at residential-level only, unless the same appliance is used by a community. DDP and DTP could enable residents to make a decision on which DSM/DR strategies to adopt, given their preferences; where preferences are expressed as maximum tolerable delay and time-range of intolerable delay, respectively. Since DDP and DTP are functions of people's schedules and preferences, and they measure customer convenience, DDP and DTP can be considered cultural indicators or tools.

In addition to the novel indicators, a contribution was made in Chapter 5 on how to estimate the value of indicators in the future given their value at an earlier time. Two methods of estimation were utilised, which are statistical mean and regression, depending on the behaviour of the indicators over time. Downsampling was also considered but rejected due to unacceptable error margin. Therefore, this contribution relied on visualising the behaviour of the indicators over time, which was achieved by calculating the indicators at every time-step of the simulation, rather than at the end of the simulation as is typical. This contribution could be used to run simulations for shorter periods, especially given resource limitation, then estimate indicators beyond the time span of the simulation, within acceptable error margin.

Other contributions include a way to generate realistic synthetic residential load profile based on average statistics of appliances (Chapter 6), a way to generate synthetic appliance-use profile based on average statistics of appliance (Chapter 6), and a simple intra-community tariff (Chapter 8). The typical approach of generating realistic residential load is to rely on Time-Use Data (TUD) which is expensive to generate and therefore usually available for a day or two only, which could make it less representative depending on the intended use. On the other hand, average appliance-use can be obtained by surveys, or even estimated reasonably from desk research. Whilst the proposed method was presented in SD diagrams, the method can be implemented (perhaps more efficiently) without diagrams, in programming languages. This contribution could simplify and reduce the cost of generating synthetic residential load that is realistic.

The same method of generating residential load profile generates appliance profile for use or power demand, which can be used as input to other simulations or to evaluate the effect of interventions like DSM/DR etc. In Chapter 8, a simple tariff algorithm for buying and selling energy within a community was proposed and this could be utilised in simulations in place of more elaborate tariff schemes, while establishing a simple fairness mechanism within the community, based on proportion of demand and supply per residence.

In the final category of contributions (Divergent Introductory), there are two contributions. The first contribution is a framework for designing and describing SA studies that are based on simulation, which was proposed in Chapter 3, and utilised in Chapter 5, Chapter 7 and Chapter 8. The framework is applicable to all simulation but has been demonstrated with SD in this thesis. The second contribution is a framework for three-dimensional classification of energy modelling tools, which was proposed in Chapter 2. The classification aims to avoid overlaps of previous classifications, as well as include Generic Software where previous classifications have focused on energy software only. This classification is the first three-dimensional classification of energy modelling tools, because none was found in the literature.

9.5 Reflections

9.5.1 Strengths and Limitations

The strengths of SD in EP can be understood on two levels relative to this thesis: in the case-studies; and as a comprehensive methodology for CEP which goes beyond the case-studies. In the case-studies, the main strength is the diagrammatic language of systems in the form of CLD and SFD, which promotes participation and transparency. However, as a comprehensive methodology for CEP, some of the strengths of SD can be anticipated by induction, pending demonstration of the whole methodology. One such strength is the facilitation of participatory and trans-disciplinary research and projects, because SD has been demonstrated as a PSM and in top-down simulation modelling within participatory and trans-disciplinary research (see Chapter 2), and PSM and top-down simulation are part of EP. Moreover, the results from the PSM exercise could be used to create or enrich a top-down model, as well as structure MCDA for decision-making by multiple participants. This participatory capability would also enable modelling of cultural factors in EP. Moreover, learning the SD modelling language is easy because even primary school pupils have been taught SD successfully [366].

As a comprehensive methodology, the first limitation is that SD cannot be sufficient for the entire CEP phases, especially where there are multiple participants because MCDA is required in Phase III. Whilst SD is not suitable for accounting models in Phase II, accounting models are not necessary for CEP. However, SD can be sufficient for CEP when there are no multiple participants because decisions can be made by a single expert/perspective/stakeholder. Another limitation is that SD does not model optimisation based on meta-heuristic algorithms (nor machine learning) which are commonly used in bottom-up simulations, because SD is a simulation method not an optimisation algorithm. However, simulation-based optimisation is available as an alternative, and has been discussed in Section 2.4.4.4.

9.5.2 Insights

In addition to what has been discussed, some insights were gained through the research process. The main insights to be discussed involve three areas: framing and problem-solving; downsampling and error; and choice of conceptual tools and validity tests. Framing and problem solving will be discussed first. Through the process of modelling in the different case-studies, some insights were gained on problem-solving in general and on SD modelling in particular. The available options for solving a problem are largely determined by the conception of the problem. In the case of SD, the tools of conceptualisation are CLD and SFD. Anything can be conceptualised as a system using CLD. On the other hand, SFD is more specific, conceptualising systems in terms of stocks and flows, which may be caused by other variables. Nonetheless, there is a relationship between the tools of conceptualisation in SD and the novel contributions made in this thesis.

Conceptualising the RES using SFD made some novel contributions more obvious, and perhaps explains why previous works may have overlooked it. For example, the concept of ‘conserved flows’ in SFD made the graphical identification of energy conservation more obvious (Chapter 4). Furthermore, modelling non-linear efficiency is obvious in SFD because non-linearity is encouraged where appropriate (Chapter 4, Chapter 5 and Chapter 8). Related to non-linear efficiency, proposing ELR (Chapter 5 and Chapter 8) was obvious as an indicator because the losses were already conceptualised as stocks, which means they were measured cumulatively at every step of the simulation. Having the losses measured made it easier to consider calculating its proportion to the total energy generated, which is ELR. Furthermore, analysing the behaviour of indicators over time was also obvious because the behaviour of variables is important in SFD. Observing the behaviour of indicators led to the contribution of estimating future indicators based on its past behaviour. Finally, the complexity of integrating TUD to SFD in order to simulate residential load encouraged exploring simpler methods, and eventually led to the contribution that average appliance-use data could suffice.

The second area of insight is the implication on downsampling on the accuracy of time-dependent variables (e.g. power in W) in models and even real-world measurements. The error resulting from downsampling will persist as long as time is discretised. Downsampling was used to explain the quantitative difference between the SD model and measurements from real residences in Chapter 4. Downsampling was also explored as an option for estimating future performance of a simulation model in Chapter 5. From the beginning of the research project, it was assumed that models are never perfectly accurate, which explains the expected error in variables between a model and the system it models. Whilst it was obvious that the accuracy of a model is relative to a measurement of the real system, it was not obvious that the measurement is not perfectly accurate relative to the phenomenon it attempts to measure in reality. Between a model and a measurement, downsampling contributes to the error because of the averaging involved, but even more so when a model’s variable is a discrete function that depends on threshold values of a downsampled variable; this was the case in Chapter 4. Between the measurement and the real system, there will always be errors if the measurement discretises time. Time, in reality, can be considered continuous because even the highest possible resolution of time cannot make it continuous, although the error between measurement and the phenomenon would reduce in practice as the resolution increases. Therefore, measuring time-dependent variables in standard units does not make them more accurate to the phenomenon per se, but the resolution of time in the measurement would.

The third area of insight is the choice of conceptual tools and validity tests. Related to framing the problem, the choice between CLD and SFD was important. While SFDs can be created from CLDs and vice versa, SFD is less ambiguous and more detailed and recommended as SD best practice when creating a SD model. However, it was discovered that there were instances where the simplicity of CLD communicates better than SFD (conceptual models in Chapter 6 and Chapter 7) because CLD was sufficient while keeping it simpler and clearer. Similarly, it was found that some validity tests can take a different implementation when using discrete systems, unlike continuous systems which are most practiced in SD. For example, in chapters 6 and 7, it was found that testing the model for extreme values in the traditional sense of inserting extreme (non-realistic) parameters in the model was not necessary because the model is discrete. In discrete systems, extreme conditions can be explicitly controlled in the formulation (e.g. if-else statements) as in the case of rated power. Confirming that the logical expressions of the control work in discrete systems is the equivalent of testing for extreme values in continuous systems.

9.6 Opportunities for Future Research

Throughout this thesis, the effectiveness of the proposed SD-centred methodology – as a whole – has been argued inductively, by concluding that it would be effective because the identified parts of the methodology have been demonstrated to be effective. Similarly, SD integration of different methods and models have been demonstrated to work from existing literature and the case-studies in this thesis, and therefore would work in the methodology. However, the methodology remains to be demonstrated as a whole, which is crucial especially given that most systems methodologies assume that the whole is more than the sum of its parts. Therefore, the continuation of this research in its main trajectory includes demonstrating all the methods of the SD-centred methodology holistically in a CEP case-study.

Furthermore, the continuation would use the comprehensive methodological framework proposed in this work (see Section 2.6) to answer the questions raised in the preface: How does culture undermine energy technology as a solution to a problem? Can cultural factors be modelled in planning energy solutions? Whilst the explored literature highlighted situations where culture undermines the effectiveness of technology solutions (see Section 7.3.4), the how has not been thoroughly investigated. SD in the proposed methodology could explore the how in Phase I (e.g. using MM), then use that to inform the system design in Phase II (especially the incentive mechanisms in top-down simulations), then better understand the required input parameters (including socio-economic parameters like energy affordability, family size and education level) for the bottom-up simulations, and make decisions in Phase III with a clear priority of requirements obtained in Phase I.

In addition to the main trajectory, there are opportunities that diverge from the case-study chapters, which may or may not contribute to the main trajectory. Examples of these include the following: in Chapter 4, the supply-side SD model could be expanded to include Electric Vehicles that act as load or source depending on the time of day. In Chapter 5, investigation could be made into the threshold when the percentage of selling price in a ToU tariff becomes profitable, in comparison to an alternative flat tariff. In Chapter 6: model seasonal variation demand of residences; model different types of residences (e.g. single houses and condominiums) with the appropriate building envelop; calibrate the demand-side model using measured data from a single residence; and explore further constraints on total power consumed by appliances, like maximum supply to a residence. In Chapter 7, the finding that earlier DR hours (relative to midnight) lead to better sustainability performance, could be explored further. In Chapter 8, the following questions could be explored: what fraction of total residential batteries' capacity performs technically equivalent to a community battery; how does the performance of community batteries change as the ratio of prosumers and consumers vary in the community; and who benefits the most between consumers and prosumers given a community battery. Based on the above, there are many opportunities for future research depending on which trajectory is sought.

10 References

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