Hierarchical Control Framework to Exploit Community Energy Storage for both Local and System Benefit

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Abstract

According to the legally binding target for European governments, by 2020, 15-20% of the EU`s energy consumption should be produced from renewable sources. Furthermore, according to the National Grid`s estimate for future energy scenarios in the UK, by 2035/36 (according to the "Gone Green" future scenario) annual electricity demand could potentially reach 375TWh/year with the residential consumption energy forming 33% of the total electricity demand [3]. As claimed by the same scenario, Renewable Generation (RG) will represent 53% of the installed capacity and will provide 50% of the generated energy with wind and PV contributing almost 46% of the supply mix.

The combination of integrating intermittent RG, reducing fossil fuel based generation and the electrification of heat and transport (which will inevitably lead to higher electricity demand), means that if the current electricity transmission and distribution system remains unchanged, it will struggle to meet:

- Reduce Power quality
- Overloading of distribution equipment (e.g transformers and feeders)
- Increasing network losses
- Higher number of system frequency deviations
- Increased voltage unbalance
- Fault detection and Location

In systems dominated by Renewable Energy Sources (RES) the dominant challenges will be the reduced inertia of the electrical system and the associated increasing need for frequency regulation services.

Over recent years small home Battery Energy Storage Systems (BESS) in combination with solar PV systems have become commercially available and more affordable. The storage capacity of new, small scale residential BESS units (e.g Tesla Powerwall) is also increasing.

The aim of this project is to investigate how domestic Battery Energy Storage Systems can contribute to Frequency Regulation services and at the same time provide benefit for electricity end-users through achieving local community objectives such as reduction of import at peak tariff periods and increased “self-consumption” of locally generated renewable energy. Furthermore, it will explore if the creation of energy community entities can improve these.

In the process of tackling these questions a novel hierarchical control framework has been proposed which is able to exploit community BESS, for both local/community benefit and system benefit. In addition, while simulating the proposed control framework a novel electric vehicle model (EV) was developed in order to aid the investigation of future energy scenarios.

Real time data from photovoltaic systems and the electrical system frequency data were analysed and used to understand the requirement for Frequency Regulation Services. This informed the development of a novel higher level control, the Adaptive Community Power Profiler – Energy Management System (ACPP-EMS) which was able to provide local and national benefit through controlling BESS in small communities with low level real time controllers by imposing Power Profiling targets to achieve multiple objectives. Simulation studies demonstrate the benefits provided by this controller.

Acknowledgments

This Thesis is dedicated to my fiancé Ilianna Filippopoulou.

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A special thank you goes to my family for their understanding, encouragement and love.

List of Abbreviations

ANN	Artificial Neural Networks
ACPP-EMS	Adaptive Community Power Profiler – Energy Management System
ARIMA	Auto regressive Integrated Moving Average
BESS	Battery Energy Storage System
CCi	Community cell Consumption
CPPT	Community Power Profiling Target
DER	Distributed Energy Resources
DMS	Distribution Management System
DNO	Distribution Network Operator
DSM	Demand Side Management
DTPM	Distance Travelled Probability Matrix
ERi	Energy Request
ESS	Energy Storage Systems
EV	Electric Vehicle
FR	Frequency Regulation
FRR	Frequency Regulation Request
FRS	Frequency Regulation System
HHB	Half Hour Block
LC	Load Control
MAS	Maltiagent Systems
MGCC	Microgrid System Central Controller
MILP	Mixed Integer Linear Programming
MS	Microsource
NTS	National Travel Survey
PCC	Point of Common Coupling

PEV	Plug-in Electric Vehicle
PJM market	Pennsylvania, Jersey, Maryland market
PR	Primary Response
PV	Photovoltaic
RES	Renewable Energy Sources
RG	Renewable Generation
RMSE	Root Mean Square Error
ROi	Regulation Response
RRi	Regulation request
SARIMA	Seasonal Auto regressive Integrated Moving Average
SCADA	Supervisory Control and Data Acquisition
SOC	State of Charge
SR	Secondary Response
TAPM	Target Achieved Probability Matrix
ToU	Time of Use
TPM	Transition Probability Matrix
TSO	Transmission System Operator
TUS	Time of Use Survey
VPP	Virtual Power Plant
V2G	Vehicle to Grid

Contents

Chapter 1: Introduction

1.1 Introduction

By 2050 a legally binding target arising from to the 2008 Climate Change Act [1] states that the greenhouse gas emissions should be reduced by at least 80% below the 1990 baseline. One of the most significant aspects to minimize our greenhouse gas emission footprint and address sustainable development issues is the transformation of the current structure of the electrical power grid. The future electrical grid should progress towards a smarter, more efficient and modern form which is able to replace centralized fossil-fired generation with smaller localized renewable generation technologies with almost zero carbon emissions and with the ability of control load demand, in order to optimize the use of local energy generating resources.

According to the legally binding target for European governments [2], by 2020, 15-20% of the EU`s energy consumption should be produced from renewable sources. Furthermore, according to the National Grid estimation about future energy scenarios in the UK, [3] by 2035/36 (Gone Green future scenario) electricity annual demand could potentially reach 375TWh/year with the residential consumption energy corresponding to about 33% of the total electricity demand. As claimed by the same scenario, Renewable Generation (RG) will represent 53% of the installed capacity and will provide 50% of the generated Energy with wind and PV contributing almost 46% of the supply mix.

A large part of the Renewable Generation (RG) installed and planned to be installed in the future is based on wind and PV with their combined outcome potentially representing 85% of the total renewable generation [4]. According to [5,6,7] even with the latest developments in forecasting techniques for intermittent renewable generation systems, errors for a day ahead forecast can reach up to 10% Root Mean Square Error (RMSE). Consequently, due to the fact that forecast attempts for these intermittent generation types contains high errors due to their variable nature, extra balancing resources need to be deployed by electricity organizations in order to remain within the predetermined quality standards.

In a scenario researched by Dale L. et al. [8] traditional gas-fired plant and wind generation are compared, with the conclusion that for an installed 26GW wind generation capacity only 5GW of conventional capacity is displaced. Furthermore according to [4], based on an assumption of 1500 MW of installed wind capacity in Ireland, the conventional reserve requirements for a forecast horizon bigger than 6 hours is almost 33% of the installed capacity.

The combination of integrating intermittent RG, reducing centralized fossil fuel generation installations and the electrification of heat and transport (which will inevitably lead to the growth in electricity demand), means that if the current electrical system remains unchanged will be struggling to address issues of:

- Power quality
- Distribution transformers and feeders overloading
- Network losses (increment)
- System frequency deviations
- Voltage unbalance
- System protection

In systems dominated by Renewable Energy Sources (RES) the dominant challenges will be the reduced inertia of the electrical system and the associated increasing need for frequency regulation services.

In recent years small home battery energy storage solutions (BES) in combination with solar PV energy production systems are becoming commercially available and more affordable [9,10,11] . The newest of the offered Battery ESS, the tesla powerwall [9] with a 14 KWh capacity and 5KW real power output is offered at £5900 with all the supporting equipment included and 10 year warranty. Similarly, MOIXA [11] is offering as a package, a 2KWh battery and a 2KWpeak PV systems with all the installation and inverter costs included at a price of £4995.

These Battery Energy Storage Systems (BESS) are presented as an ideal solution for households to minimise the cost of import energy through capturing and storing excess locally generated renewable energy during the high generation periods and use it when ‘‘the sun is not shining’’ [12]. Thus, the homeowners with installed BESS are able to minimise their reliance on its energy provider, can save more money on his energy bills, be less effected by price hikes and at the same time maximise the consumption of their self-generated energy.

For the above mentioned reason and due to the fact that small home ESS are becoming more popular, a number of hypotheses were made:

- Can home installed BESS provide benefit for both the electricity end users and DNOs /TSOs?
- Can the higher capacity from newer small-scale BESS to be used for ancillary services such as Frequency Regulation?

- Is it possible for end users to be rewarded for providing Frequency Regulation (FR) services?
- Can a bigger benefit be achieved if the end users operate as an energy community rather than individuals?

1.2 Aim and Objectives

The aim of this project is to investigate how domestic ESS can contribute to FR and at the same time provide benefit for electricity end users.

In order to achieve the project aim, a number of key objectives had to be developed and tested:

1) Creation of a novel control framework which can exploit community ESS, for both local community benefit through energy import cost reduction and at the same time being able to provide to grid operators ancillary services.
2) Create a novel higher level control algorithm as part of the proposed control framework able to provide local and national benefit through the exploitation of small scale community ESS
3) Analyse economically how using ESS for both local supplier and FR can provide extra benefit and make them more appealing as an investment.
4) Develop suitable models and data to support the analysis.
5) Provide a methodology for calculating the required battery size (aggregated) to achieve the aforementioned objectives.

1.3 Thesis Structure

The following chapters are organised as follows:

Chapter 1: Introduction, Project Aim and Objectives

Chapter 2: Literature review, includes previous works and solutions provided to address the problem of electricity expenditures, energy efficiency and provide solutions for frequency regulations ancillary services.

Chapter 3: Proposed framework, includes details about the novel proposed framework and a new proposed frequency ancillary service to complement the currently existing ancillary system.

Chapter 4: Modelling techniques and data sources, where the developed and used models through the simulation procedure are introduced in detail.

Chapter 5: The novel proposed and developed ACPP-EMS control algorithm as part of the proposed framework is introduced.

Chapter 6: The different simulation scenarios, results and economic analysis for the different proposed strategies is presented

Chapter 7: Conclusion, where a synopsis of the results are summarised and the project main achievements outlined.

Chapter 2: Literature Review

In the last decade more and more attention has been directed towards the integration of renewable – intermittent energy sources onto the electrical power network, not in the form of uncontrollable generation but as dispatchable resources which are able to provide power to the network in a more efficient and predictable manner.

For these reasons in [13] and [14] energy storage systems where combined with Solar Photovoltaic (PV) and Wind Turbine systems in order to smooth the output generation and provide energy shifting services to the network during high demand periods. In fact in [13] a control algorithm was developed to control a battery energy storage system in order to compensate the difference between the produce power and a power level agreed in advance, based on forecasted generation for the next hour with a 10% error. In a similar way in [14] a hybrid energy storage system composed of a fuel cell combined with an electrolyzer and a pumped hydroelectric system was used together with a wind farm to create an optimization problem with the goal to satisfy the hourly variable electrical loads and decide the best use of the different energy storage forms.

In contrast, Demand Side Management (DSM) has the same targets as the ones stated for ESS but follows a different approach to reach its goal. In principle, any measure that can be taken by generating units to ensure that electricity generation and load are equal has an equivalent countermeasure that can be taken by loads (the demand side) [15]. For residential buildings and commercial properties, the control of a large number of non-essential or thermostatically controlled loads including in the near future Plug-In Electric Vehicles (PEVs) (that will account in the United States about 25% of the total automobile sales by 2020 [16]), can provide to the system a faster response than traditional generating units and overall lower emissions (by avoiding the use of inefficient generation units during periods of high demands) leading to an easier incorporation of Renewable Generation.

At the low voltage level especially, residential Battery Energy Storage Systems (BESS) are considered as the best solution to incorporate small roof mounted solar PV energy systems to the electrical network and a number of studies [17, 18, 19] revolves around the economic viability of such solutions.

2.1 Residential PV and BESS Economic Viability

Currently commercially available BESS provided by a number of well-known manufacturers [9,10,11] are promoted as being the ideal combination to have with residential solar PV generation systems in order to maximise PV installation potential by storing excess energy during the high generation periods and using it when ‘‘the sun is not shining’’ [12]. Thus, the BESS owner is minimising its reliance on its energy provider, can save money on their energy bills, be less effected by price hikes and at the same time maximise the consumption of their self- generated energy.

In order to achieve the aforementioned results, the energy storage systems manufacturers usually suggest a "greedy" [17] control algorithm, where the BESS is set to store the PV-generated surplus energy and release it as soon as the household load exceeds the PV-system generation. According to Sharp [10] the combination of PV system and battery storage can cover up to 80% of the needs of a household, depending on the season.

To investigate if the above claims and research if the available BESS are economically viable in the current market, a number of different scenarios where investigated by different researchers. In a paper by J. Weniger et al [18] a lithium-based battery ESS was considered with a calendar lifetime of 20 years or 5000 cycles. The control BESS scheme used, was a simple excess energy ‘‘greedy’’ controller as described in the previous paragraph.

The test load profile was created for a single –family household in the north-east of Germany from several typical daily one minute load profiles as one minute average values. The entire year electricity demand was determined to be 4MWh. The average retail for electricity price (simulation period) for the next 20 years including VAT was estimated to be 0.34 €/kWh (0.3 £/kWh). The average electricity price result was based on a current electricity retail price of 0.28 €/kWh with a 2% increase over the next 20 years.

One of the scenarios tested and the most interesting in terms of the current situation was the ‘‘today’’ scenario. According to that, the current residential PV system cost is about 1800 €/kWh and the injection of energy to the grid that cannot be absorbed by the BESS is reimbursed with 0.15 €/kWh. Furthermore, the cost of a lithium-ion based battery ESS is in the range of 3000 €/kWh. The results of the analysis for the described scenario is presented in Figure 2.1. The nominal PV power and the usable battery capacity are normalised to the annual year load demand of the single-family typical load profile used.

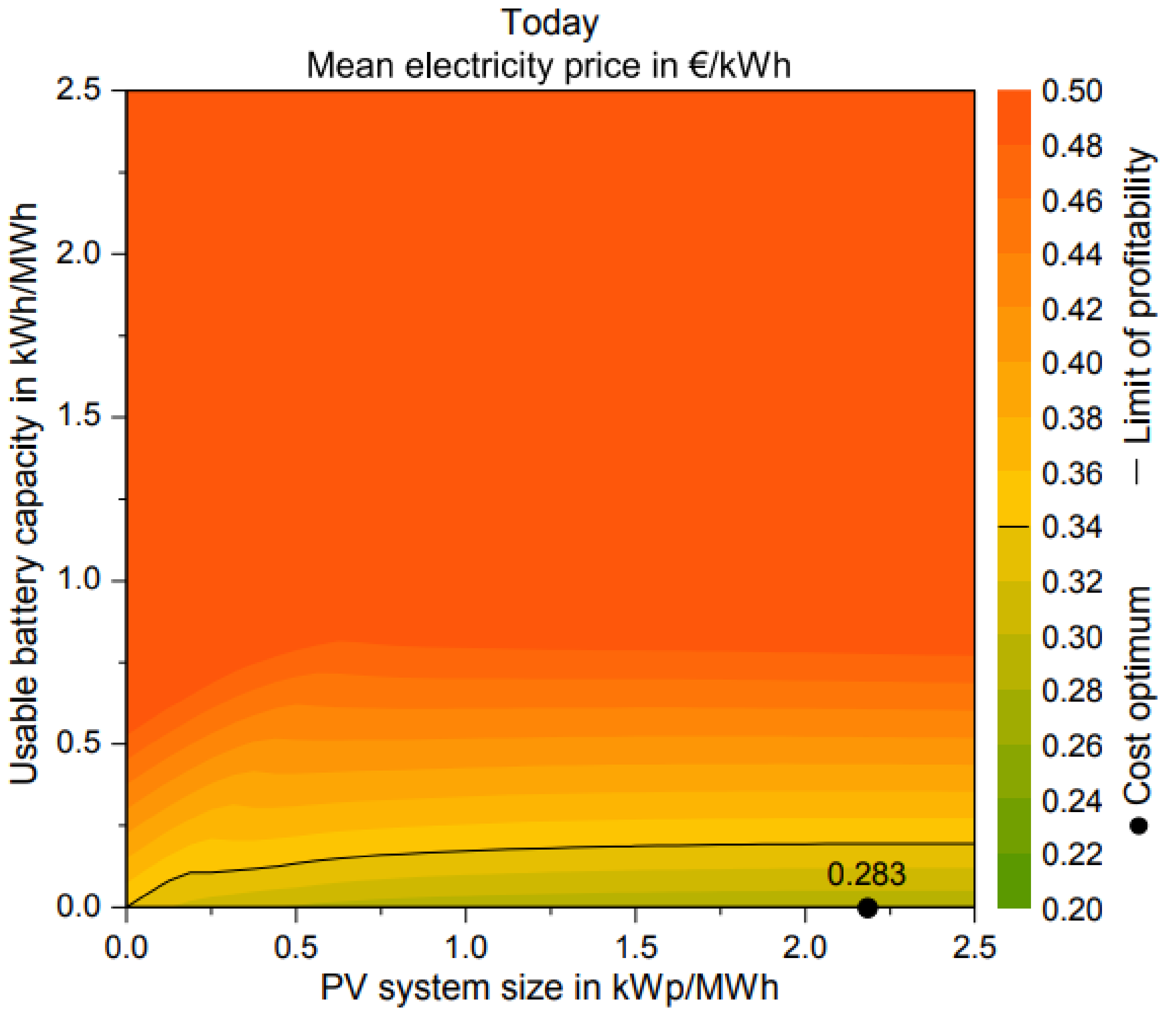

Fig 2.1 Mean electricity price at present (‘‘today’’ scenario) in dependence of the PV System and battery size. [18]

As stated in the analysis by J. Weniger et al [18], the average retail electricity price for the next 20 years, the lifespan of the PV and BESS, is estimated at 0.34 €/kWh. The investment of a PV and BESS system is considered to be beneficial if the average electricity price of the configuration is below the average retail electricity price. In Figure 2.1 that is introduced as the limit of profitability and is indicated with the black line.

Based on the values assumed for the ‘‘today’’ scenario, the optimum solution with the lowest electricity cost is a PV system with a 2.2 kWp/MWh and no BESS indicated with a black dot on Figure 2.1. Furthermore, it can be noticed that according to the analysis results, any attempt to couple a BESS to the PV system will result in a huge increase in the cost of electricity. If that BESS is relatively large scale, the average electricity costs will rise to about 0.50 €/kWh (red colour) in order to provide an economically viable system, making the configuration of a PV and BESS from an economic point of view not viable.

Nevertheless, for the previously used analysis, one may argue that the BESS cost used in the ‘‘today’’ scenario is considered high and that is the reason why positive financial returns are not achievable. Currently the newest member of the lithium-ion based BESS for residential use, is the novel battery system announced by Tesla motors with a cost of about 450 £/kWh [9]. In order to analyse the economic benefit of the Tesla Powerwall BESS for end-users C.N. Truong et al [17] assessed the system in Germany.

To simulate a typical single-family house in Germany with a rooftop PV system, a load profile consisting of the average 15 minutes load values of 100 measured single-family households was used. The average year consumption was scaled from 1000KWh-10000KWh to cover as many scenarios as possible. In addition, in the simulated scenarios the PV-system size was varied from 1 to 10 KWp. The total system life span is assumed 20 years. Although Tesla is providing a system warranty for the BESS for only 10 years, in the simulations conducted for 20 years lifespan, battery capacity degradation is taken into account. The control BESS scheme used in this work was also a simple excess energy ‘‘greedy’’ controller as described previously.

The reference scenario for comparison purposes as presented in [17] is given in Table 1.

Table 1 Overview of BESS reference scenario [17]

Name	Reference Scenario
Coupling	DC – coupling (5000 €)
Aging parameters	5000 full cycles until 80% remaining capacity
Subsidy	Funding of 30% of the BESS. 50% feed in limit

According to the reference scenario as presented in Table 1 the coupling of the BESS is made on the DC side directly with the PV system. A 30% system subsidy of the total system cost is provided by the German government and a limit of feeding to grid only 50% of the daily generated PV energy is imposed. The reference scenario is based on the existing ‘‘today’’ practice followed in Germany for BESS.

Based on the reference scenario, the Return of Investment (ROI) over all the simulated PV system sizes and annual loads is given in Figure 2.2 for a constant electricity price over 20 years equal to 28.72ct/kWh (2016 electricity price) in Figure 2.2a and an increasing price scenario by 4.55% p.a in Figure 2.2b. The average and large household marks in Figure 2.2 are a household with 4500 and 70000 kWh yearly consumption respectively.

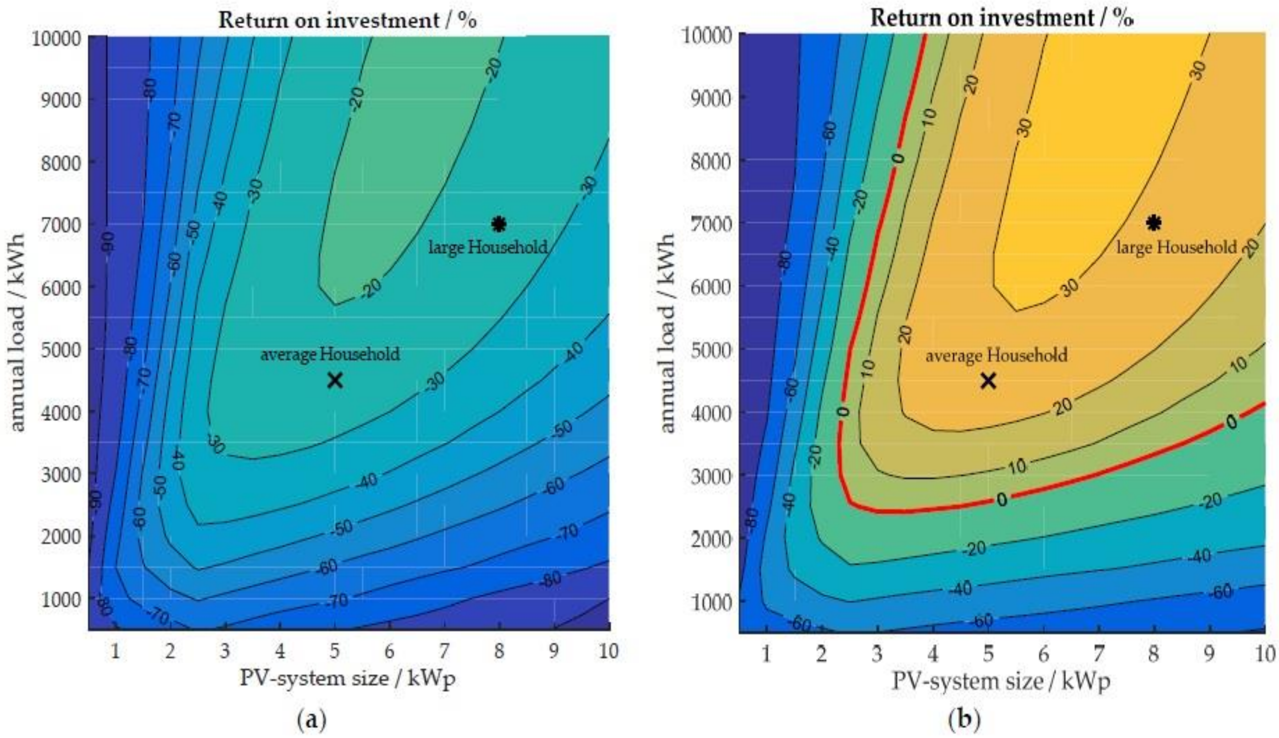

Figure 2.2 ROI of reference scenario aver all simulated PV-systems and household loads. (a) Results for constant electricity price scenario. (b) Results for increasing price scenario, The red line emphasizes the ROI of 0% [17]

As it can be observed in Figure 2.2a, although in the reference scenario a subsidy of 30% of the total cost of the BESS is provided, the ROI in all the cases is negative resulting in financial losses when installing a BESS. The constant price not only does not allow the repayment of the investment but leads to high losses.

In contrast because of the highly increased price in Figure 2.2b, some scenarios are above the red line which represents the limit of profitability and becomes economically viable with a ROI of about 25% for the two marked households. As stated before and its needs to be emphasized again, the above results have 30% of the total cost of the BESS subsidised.

A different assessment for BESS that can create a positive predisposition to verifying our hypotheses of the benefit for using the BESS for frequency regulation purposes as presented in Chapter 1 is introduced by Avendano Mora et.al [19]. According to the published results, lithium–ion BESS are compared in terms of economical assessment in a frequency regulation market in the USA using historic clearing (published) prices from 2012-2014.

The PJM market used is a two-fold market and payments are received based on capacity but also performance. The capacity payments are based on the clearing prices and the performance payments are based on the accuracy of providing the Frequency Regulation Request (FRR) service and are also market based. The BESS used are assumed to have a high performance of 93-98%.

Based on the financial performance results provided a 250 KWh system will recover the cost of the original investment and start producing profit for its owner after 7 years while a bigger 500KWh system has a payback time of 6 years. Based on the presented results it can be assumed that our hypothesis that being able to provide frequency regulation services at the same time as minimising the cost of import energy through energy shifting can make residential small-scale BESS become more attractive as an investment.

Overall the provided evidence in the investigated scenarios presented in this section, provide a strong indication that although the cost of BESS is becoming lower, the usage of the systems as they are marketed by their manufactures are rarely economically viable and beneficial for the end-user. The only scenarios that can provide some benefit for the users as it can be observed in the analysis presented by Truong et al [17] is through cost subsidies and with highly annual increasing electricity costs.

2.2 Proposed Management Systems available in the literature

An attempt to overcome the presented problems and take better advantage of small scale residential energy storage systems by implementing a more holistic approach is presented through management systems known as microgrids or Virtual Power Plants.

A microgrid is defined as an aggregate of small scale Distributed Energy Resources (DERs) such as photovoltaic panels, wind turbines, micro gas turbines and electric storage systems [20] that are miniature versions of the main electrical power system. These miniature electrical systems usually have a single connection point with the rest of the grid and are able to work in an isolated or "island" mode when required or when it is more beneficial in order to achieve their targets.

Microgrids according to their energy supervision systems follow centralized or decentralized control strategies in order to achieve local goals which mainly focus on cost reduction, reliability, efficiency and power quality while successfully integrating local production sources.

These management systems according to [21] comprise of four key components:

- A Supervisory Control and Data Acquisition (SCADA) system for the measurement and the analysis if required of the collected data.
- The real time decision part of the controller, to be able to take decisions based on the managements system objectives and available data.
- The communication part, for transmitting the decisions between the controller and the equipment.
- The local devices controllers, to receive and execute the decisions.

Currently a number of microgrid management system are available in the literature with different degrees of complexity to address the control problem. In [20] a detailed and clear presentation of the control system is given, as a Mixed Integer Linear Programming (MILP) problem providing lower operational cost, higher level of efficiency and extended battery(storage device life). MILP was chosen because of its advantage of using limited computational resources making it suitable for real time control implementation. MILPs or variations of MILP systems are one of the most frequently used real time control algorithms found in the literature for this type of applications [22, 23,24] .

Another very capable centralised control system developed by Fazeli et al [25] following a deterministic control algorithm approach, is a novel power flow control algorithm for real time dispatch of distributed energy resources. The control algorithm is responsible for following target values as the communities' optimum solution to achieve its objectives given from a higher hierarchical level. According to published results, the algorithm was capable of operating in real time, controlling a large number of devices and distributed generation including ground source head pumps, refrigerators, energy storage systems and small-scale distributed generation in a 100 house community.

A different decentralised approach is presented in [26]. The microgrid control is based on a Multiagent System (MAS) with each agent controlling small production or consumption units. The main objective of each agent is to maximise each unit's benefit, and by doing that minimise the overall operational cost of the microgrid. By implementing a multiagent control methodology, due to the system structure, solutions are obtained to a number of problems, mostly towards the fact that the production or consumption units might have different owners or that each agent can ensure the uninterrupted energy supply of some local critical loads and better voltage control.

The kernel of the system is an auction algorithm where each agent, based on its local information about the unit it controls, bids. After a number of iterations, it has an "object-load, generation unit target" assign to it and the algorithm converges to the optimum solution. However, despite all the positive aspects of the algorithm a major drawback is that is not able to handle more than 30 "objects" because more than 100 iterations might be needed in order to reach a solution and negotiations might last several hours.

A different approach is given in [27]. The main objective of the proposed solution is to maximise the profit of the VPP through the dispatch of Renewable Energy Sources (RES), hence optimal power flow. The profit maximisation according to the article is achieved with the help of a genetic algorithm which is based on filtering a random generated solution that lies in the feasible solution area until it reaches the optimum. The controller attempts to imitate the Natural Selection on the Darwinian thinking of the biology of evolution.

In order for the above real time control solutions to be implemented, low cost home monitoring and recording systems need to be installed. Fletcher et al [28] developed a low cost hardware and software solution making use of existing hardware able to control main electrical devices. The system concept is presented in Fig. 2.3

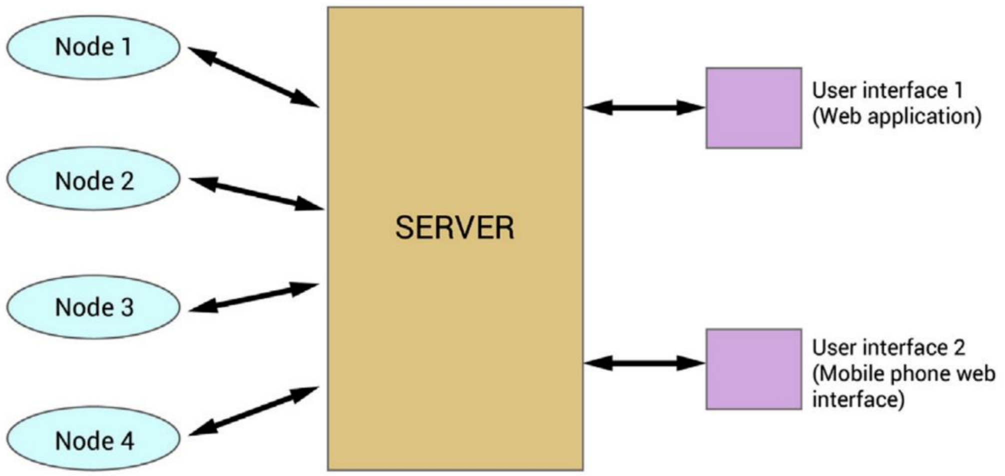

Figure 2.3 Overall system concept [28]

As it can be observed in Figure 2.3 the system was developed having in mind to allow the users to switch devices around the home through the web. The system consists of a single server responsible to monitor a number of attached devices. Although the system visualized and the prototypes were developed to provide the ability for users to control their "smart home", it provides a clear indication that existing technological solutions for device controlling are mature and can be implemented and used with a number of control algorithms.

Despite the fact that real time control algorithms are out of the scope of this project, this section was used to present the range of solutions provided for demand side management and BESS real time control. Considering that this part has been studied to a satisfactory degree and the proposed solutions are considered adequate for a limited number of control devices in small communities (microgrids), in the next section a number of proposed hierarchical solutions are presented to address the limitations of real time controllers.

2.3 Hierarchical control frameworks

Currently a limited amount of hierarchical structures exist in the available literature able to address the problem of smart grid control on a larger scale and maximize the benefit that can be achieved. Through the proposed hierarchical structures, [30,31,32,33] different techniques to optimize predefined goals are presented in the following section. In [29, 30] a transactive hierarchical control structure is proposed as seen in Figure 2.4.

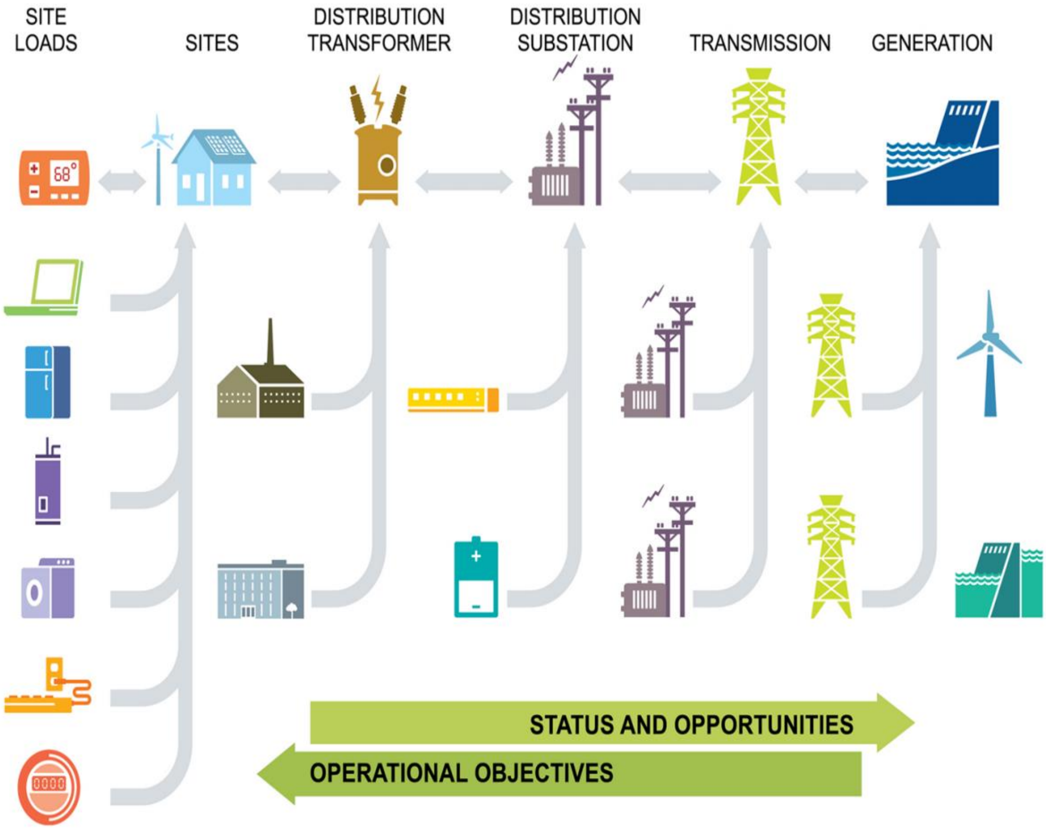

Fig. 2.4 Representation of proposed hierarchy for a hierarchical transactive control system [30]

According to the approach used, each physical point of the electrical system where demand can be predicted and aggregated is defined as a node. In Figure 2.4 these are represented, starting from the lower demand aggregated request and moving upstream from the sites (Houses), distribution transformers, distribution substations up the system generation units.

By representing the physical system as nodes, a tree form graph is formulated. Through the graph two value signals will move in opposite directions, the "operational objective" signal will move downstream towards the loads side and the "status and opportunities" demand capacity signal will flow upstream.

The value signal, shown as "operational objective" in figure 2.4, is essentially a price signal in the form of a time series for the predicted energy price over the next 24 hours. Each node will be able to modify it to serve its own operational objectives. If for instance a node at a future interval wants to avoid a constraint, it might chose to increase the price during that time period. The price is calculated using information obtained from its parent nodes. Likewise, the demand signal, presented as "status and opportunities" in Figure 2.4, will also be a time series signal for the next 24 hours that will represent the predicted demand in kW. Similarly at each node the signal will be the aggregation of the predicted demand from the downstream nodes.

The proposed system is very complex, with high communication requirements and an "intelligent" control machine as well as a demand prediction machine required at each node of the system. Moreover, as proposed by the author, the control machine of each node can be different without providing any controlling function solutions and treating each node as a black box. In combination with stated demand prediction, the requirement for an extra layer of complexity is added to an already very complex system.

In a similar way in [31] the proposed scheme addresses the large-scale characteristics of the problem. As presented in Figure 2.5 the optimization problem is decomposed in to three smaller problems resulting in a three-level hierarchical architecture.

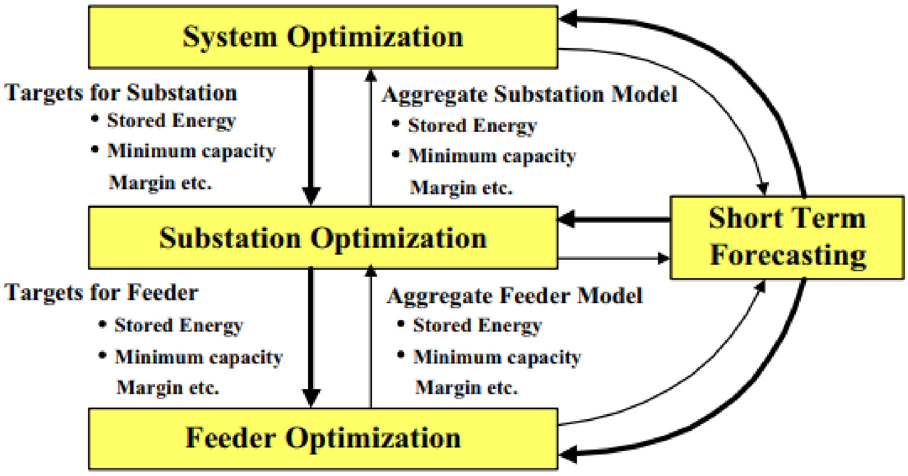

Fig. 2.5 Proposed hierarchical optimization approach for an integrated hierarchical smart grid control [31]

The first level or feeder optimization is a real time controller that determines the operating conditions of the DERs to meet the targets of the higher level or substation level, based on the higher level targets and provided forecast information to achieve the minimum operational cost. The substation level in turn is responsible for controlling 2-12 substation feeders and should be able to provide each feeder the directives (targets) that each one needs to follow, to ensure optimal operation with a larger time horizon. Accordingly, the higher level or system optimization level needs to generate target values for each substation to achieve a whole system optimal operation.

The proposed controller scheme, although clear and transparent in terms of hierarchical structure, it fails to state how the intermittent nature of DERs and the needed forecast load and generation forecast techniques and the accompanied error at every level of the hierarchy will be incorporated and used into the proposed algorithm. Furthermore it fails to explain clearly how the targets for each of the controlled feeders such as the substation optimization are going to be divided among them.

A different approach is proposed in [32]. The incentive behind the microgrid operation is to maximize the production of local generation and control the power exchange with the grid based on economical market criteria. Through the proposed hierarchical structure introduced in Figure 2.6 the writer clearly describes a hierarchical architecture that comprises of three levels.

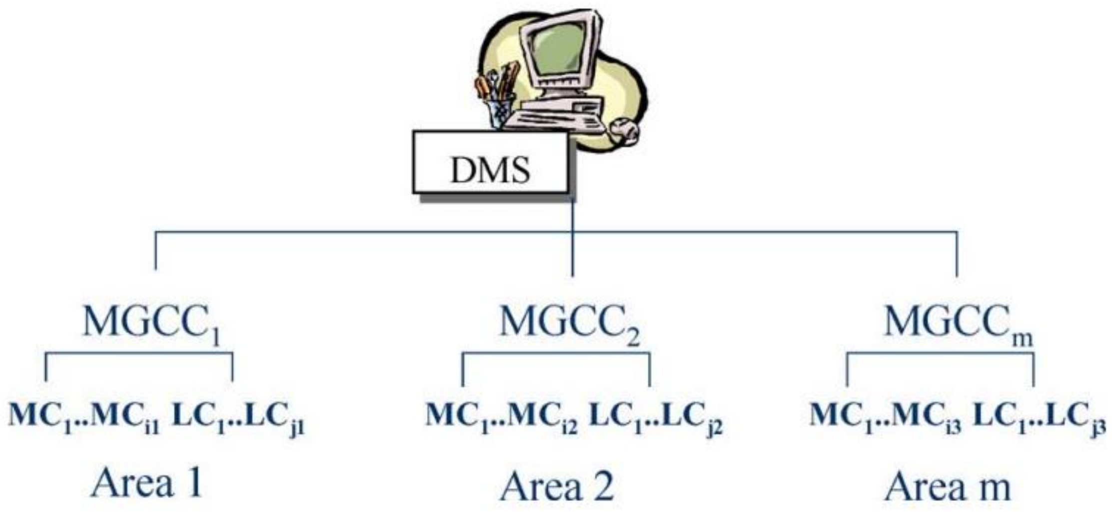

Fig. 2.6 Proposed hierarchical control structure using a centralized control for optimizing a microgrids operation [32]

According to the introduced hierarchy in Figure 2.6, a lower Microsource (MS) or a Load controller (LC) which exists at each asset of the microgrid will follow the demand target of the mid-level Microgrid System Central Controller (MGCC). The MGCC in turn, is responsible for the optimization of the microgrids operation based on market prices and limitations of the distribution system. Finally the Distribution Management System (DMS), is the higher hierarchical level of the architecture and will be responsible for the operation of the microgrid in relation to the electrical network. At this level the microgrid under control is considered to be connected to the feeder of a distribution transformer.

The operation of the controller scheme is based on the concept that each MS publishes a price (bids) for an hour into the future in small m-minute time periods. These price bids are based on the energy market prices, the needs of the facility it is installed on, the operating cost of the controlled generation unit plus a profit. After the price bids are received by the MGCC and based on the energy market prices, the forecasted loads and the published prices by each MS, the controller optimizes the microgrid operations.

This is achieved by dispatching signals to both the MCs and LCs determining the level of production for the control generating unit's levels and curtailing local loads if required. The optimization procedure is directly linked to the market policy adopted by the MGCC. The two proposed market policies are the open market, where the goal is the maximization of the profit by trading power according to the open market prices and the maximization of self-consumption, by using the local production to serve the load as much as possible.

Although the structure of the system is described clearly and the distinction between the lower unit level and the higher centrally control level is clear, many issues are not examined and remain unclear. The actual control algorithms are not provided at either level of the architecture making the system unclear. This is really important at the lower level as according to the proposed structure each microsource in the microgrid should be in a position not only to predict their future generation for the next 1 hour in small intervals (something computationally intensive and with large errors at a device level), but also provide pricing bids for each of those small intervals. This should be achieved through a device controlling algorithm making the whole system very complex.

An also very important issue identified, is that the system proposed architecture is immensely demanding in terms of system communication requirements. Market prices, load to be served and shed and set – points for microsources should be published to each low-level device while at the same time offer price bids and demand side bids from not critical loads should be sent towards the MGCC microgrid central controller. Finally safety issues such as voltage and power flow within thermal limits are completely neglected.

A multiagent based hierarchical control framework similar to the one proposed in [32] is presented by Harmouch et. al. [33]. In this control approach, the main objective is to minimize the power exchange with the grid and provide active power support to the distribution feeder of the controlled microgrid. The proposed hierarchical management levels are presented in Figure 2.7

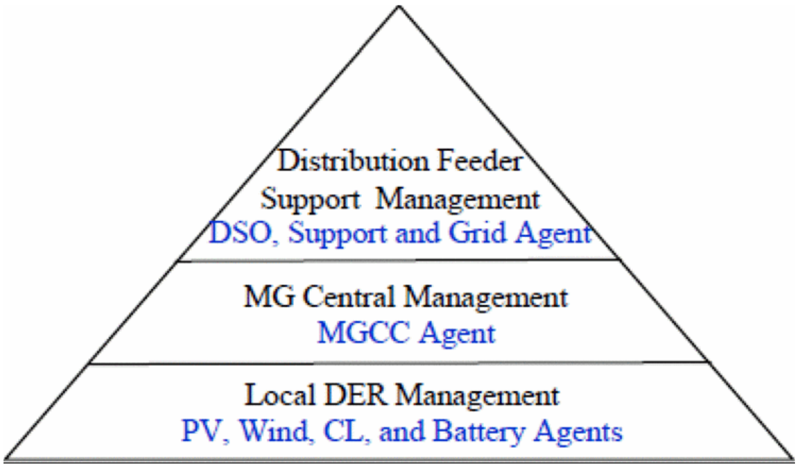

Fig. 2.7 Proposed hierarchical control management levels for a multiagent based hierarchical control for microgrids [33]

According to the proposed hierarchy the first local control level represents the agents of the controlling devices of the microgrid. These are agents of PV systems, wind generators BESS and controllable loads. The second level consists of the MGCC agent which is the brain of the microgrid and performs the power dispatch targets for each local device agent. This rule based real time controller performs power dispatch every minute. The third and highest hierarchical level in turn, includes the DSO (distribution system operator). The DSO is firstly responsible to aggregate and communicate the aggregated power the microgrid will exchange with the electrical grid and secondly if the feeder of the microgrid exceeds its maximum limitation at the PCC, inform the MGCC to provide active power support.

Although the presented work adds the element of active power support and more clarity in terms of MGCC control algorithm when compared to [32], it inherits the problem of the high computational complexity for each device agent. Each agent of a controllable device at the first hierarchical level should be able to predict their future generation or load demand which is not only computationally intensive but also introduces large errors.

In contrast with the previous presented hierarchical structures a number of authors [34, 35, 36, 37] proposed the usage of Vehicle to Grid (V2G) method for regulation purposes. A V2G system, coordinates the charging/discharging schedule of EVs batteries so that they can act as energy storage systems. Nguyen et.al. [34] proposed the usage of the onboard batteries of Electric Vehicles (EVs) having as main objective to provide ancillary services and specifically frequency regulation support services. According to their proposal the EVs batteries can be utilized as response tools in charging or discharging mode to support frequency violations. The proposed hierarchical control structure for frequency regulation through connected EVs in smart grits with renewable generation is presented in Figure 2.8.

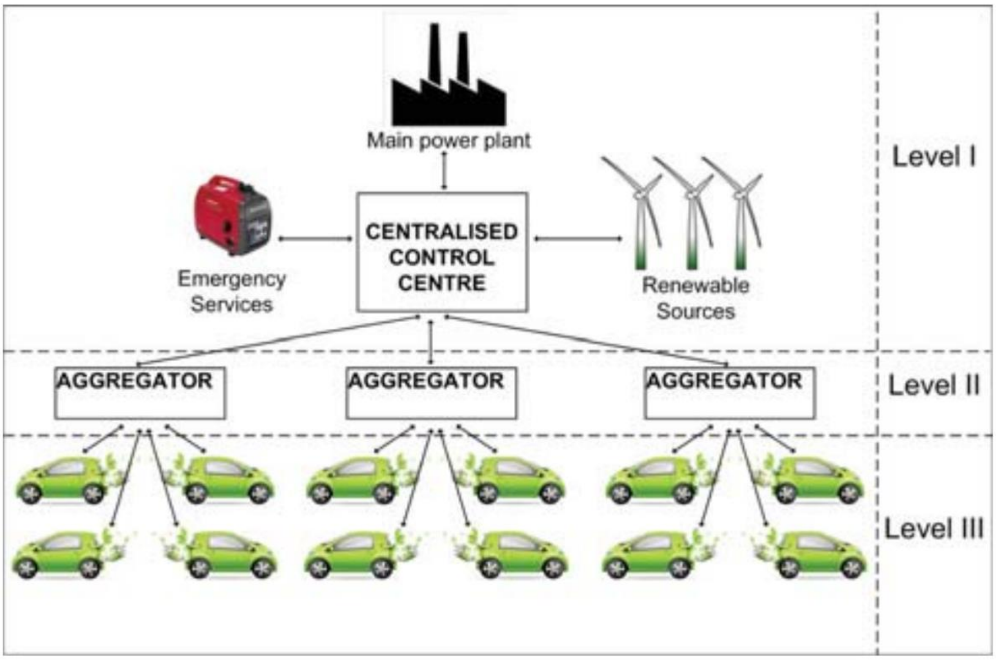

Fig. 2.8 3-level hierarchical control structure for frequency regulation support services. [34]

According to the proposed structure in Figure 3.7, at level I (the economic power dispatch center) a deterministic optimization problem is solved with the objective to minimize the operating cost of the system. From the higher level point of view, each of the lower level aggregators can be seen as a single BESS. When an EV arrives and connects the vehicle to the grid, the desired SOC at the unplug time and the actual unplug time of the vehicle must be stated.

At every time step the level II (aggregator) collects information about the connected level I EVs, their owner`s requirements and their current State Of Charge (SOC). Based on the previously run optimization at level I and their allocated power, level II aggregators will run their own optimization algorithm taking into account each vehicle`s individual parameters as stated by the owners. Once the aggregators (level II) results are obtained, the outcome is published to level I to execute the economic optimization problem for a second time. The level III (EV controllers) are each individual vehicles control unit, responsible to charge or discharge the vehicle following the aggregators recommended power rates in order to support detected frequency violations.

The presented framework provides a hierarchical control solution able to provide real time frequency control and reduce the requirement of expensive emergency backup generation due to the high penetration of intermittent renewable energy forms. According to the simulated scenario with 4 Aggregators, 1000 EVs, 40% base demand renewable resources, an emergency generator of 33.28 MW and a 33.24 MW base load, the system cost, for a 12 hours simulation window, was reduced by almost $3000 due to minimizing the usage of the costly emergency generation.

Although the proposed framework requires from each individual owner to provide exact information about usage of EV and the time the vehicle is leaving the system (making the solution difficult to implement in real life), at the same time it presents the potential of using local energy storage systems for different applications other than just energy shaving solutions.

Another centralized control scheme to support frequency regulation through V2G is proposed by Kang et al [35]. The real time scheduling technique proposed as seen in [34] also assumes that the preferences of each EV owner are stated when the vehicle is connected to the grid. The proposed real time frequency regulation systems adjusts EVs charging schedule through price manipulation. If for instance up-regulation (increase demand) is required, the real time EV charging system will increase the demand by encouraging more EVs to start charging through reducing electricity price. On the other hand, for down-regulation (reduce demand) the real time system will increase demand.

A different decentralized approach using V2G architecture for frequency regulation was proposed by Lin et al. in [36]. The system architecture consists of three key components. The grid operator, a set of aggregators and a set of EVs. The proposed system architecture and framework are presented in Figure 2.9 a and b.

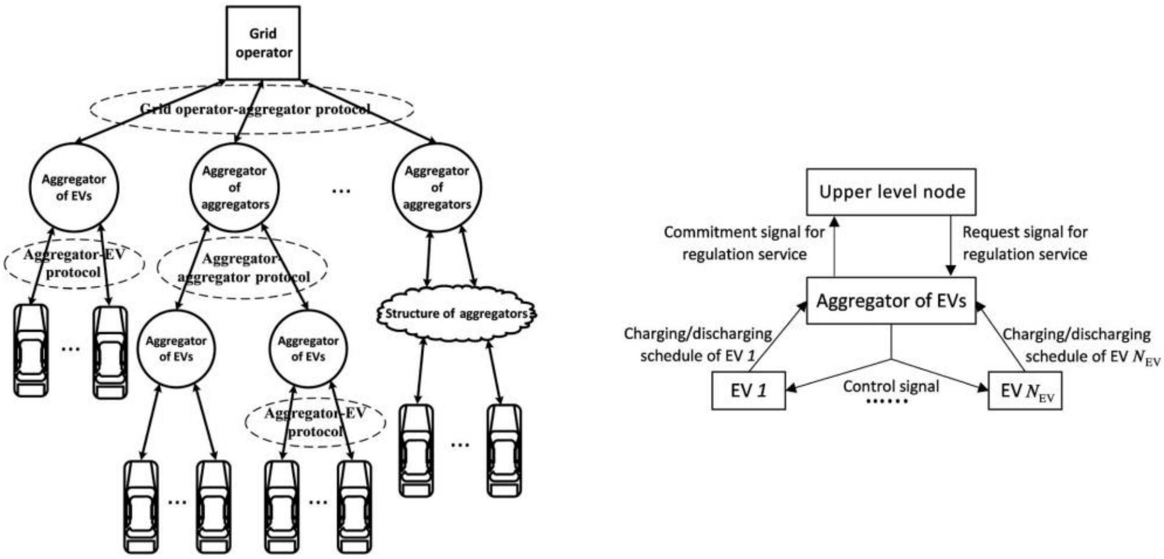

Fig. 2.9 a) Multi-level V2G system architecture b) Framework and information flow. [36]

As presented in Figure 2.9 b the aggregator of EVs receives request signals for frequency regulation from the Upper level node/Grid Operator. When the signal is received the aggregator starts to coordinate the charging/discharging schedule of EVs to meet the regulation request. Each EV controller act as an agent and the optimization is an iterative process.

In each round of the iterative process the aggregator calculates the control signal according to the charging/discharging schedules received by the EVs. The calculated signals are broadcasted to the EVs which in turn adjust their schedule based on the received signals. The

EVs new schedules are sent back to the aggregator. The iteration process stops when the predetermined criteria are met and the result is published to the Upper level/Grid operator.

Finally, a solution for frequency regulation that combines large scale BESS and EV charging facilities is proposed by Zhong et al. [37]. In [37] a coordinated control strategy based on Area Control Error (ACE) which is the system frequency deviation is presented. Depending on the ACE size the system responds differently in order to avoid influencing the EVs users. If the ACE is small, then EVs are not used and only BESS take part in the Frequency regulation. If the ACE detected is large, then both BESS and available EVs are used until supply and demand are balance and sequentially EVs and BESS return to their previous state. The block diagram of the proposed system is presented in Figure 2.10

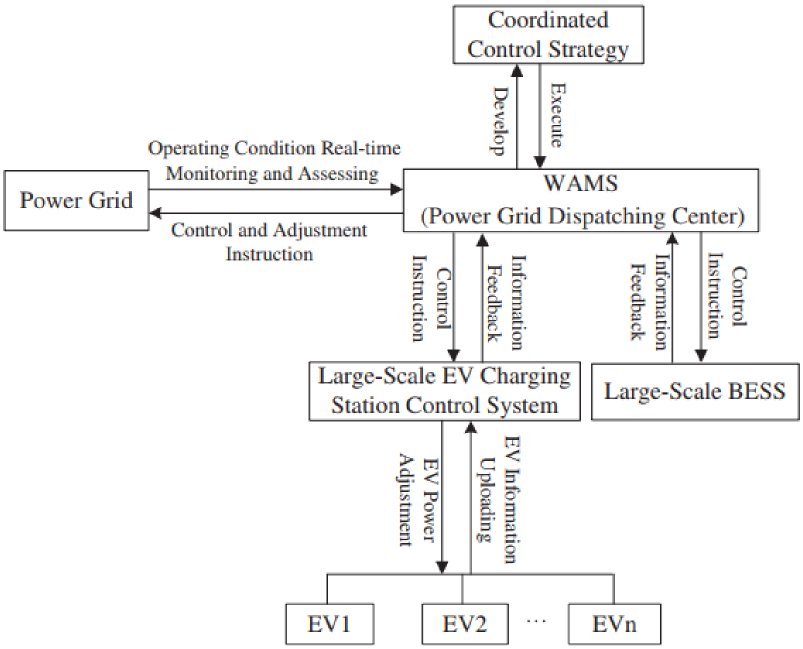

Fig. 2.10 Block diagram of EVs/BESS participating in frequency system regulation [37]

As it can be seen in Figure 2.10 a dispatching center is monitoring the power system operating conditions. EVs information about SOC and available time are collected by the EVs charging station control center, where information of all grid connected EVs gets integrated and in turn forwarded to the dispatching center. The integrated information at each charging station includes the available aggregated charging/discharging capacity and time the capacity is disposable. Similarly, the BESS feeds back the available capacity to the dispatching center. When operation of the system becomes unstable an ACE reaches the dispatching center and accordingly the Coordinated Control Strategy center the send power allocation instruction downwards to the EVs and BESS.

2.4 Conclusion

Based on the available literature as seen in the previous sections of the report, it becomes obvious that the solutions provided for the integration of DERs and the control of small communities or bigger aggregation of small scale generation and consumption is limited. From the presented solutions provided at microgrid but also on a larger scale through hierarchical frameworks the hypotheses made in Chapter 1 not considered.

In addition if we limit our scope even further to the stated aims and objectives of this project, the existing literature only addresses small specific problems. None of the proposed solutions is trying to use locally available ESS to maximise the benefit of the end user by providing both frequency regulation ancillary services and at the same time taking advantage of Time of Use (ToU) tariffs provided by energy providers through energy manipulation operating as an energy community. Furthermore, the existing available solutions as presented do not try to create a framework solution beneficial both for the system and the controlled communities.

In the following chapter the proposed framework and a new proposed frequency response service that can be introduced through the proposed framework are presented.

Chapter 3: Proposed Framework and New Proposed Frequency Response Service

3.1 Introduction

The implementation of a control system that is able to command various parameters at different levels of the low voltage electricity network is a difficult undertaking due to the complexity of the problem and the enormous signal communication burden that is required by a complex communication infrastructure. In a complex system such as this, a number of different communication requirements are present, for example local, i.e same level communication signals and mid-level communication signals between different control levels. As concluded in Chapter 2, a very limited number of frameworks are available to address the problems, in terms of controlling algorithms and communication requirements and even less are applicable or transparent

Furthermore, the management systems proposed in the literature are usually either dedicated real time controllers following a Time of Use (ToU) tariff or other economic incentives to minimise the cost of import energy for the local community or dedicated regulation market services used when the Network Operators request their assistance. In either case, solutions are usually highly specific and devised for solving individual problems.

A more general solution should distinguish between real time power balancing solutions and higher-level energy management responsibilities, implement control solutions that are suitable for each level and finally incorporate a clear and flexible design framework. The flexible design framework refers to clear same and mid-level communication requirements that leads to a scalable system and ultimately, in cooperation with an efficient and clear control strategy, to an overall optimal system operation. The proposed hierarchical framework is trying to address the problem using a bottom-up approach. The framework is presented in more detail in the next section.

3.2 Proposed Framework

The proposed hierarchical framework consists of three distinct parts with each one having different responsibilities and roles within the overall framework structure. The low level real time community controller, is responsible for the real time power balancing, the higher level community profiler which acts as an intermediate between the lowest and the highest framework level, is responsible for creating the power targets for the lower community controllers according to the energy management objectives and finally the highest level the, Distributed Network Operator (DNO) level, responsible for the overall operational health of the entire electrical grid. The framework described is illustrated in Figure 3.1.

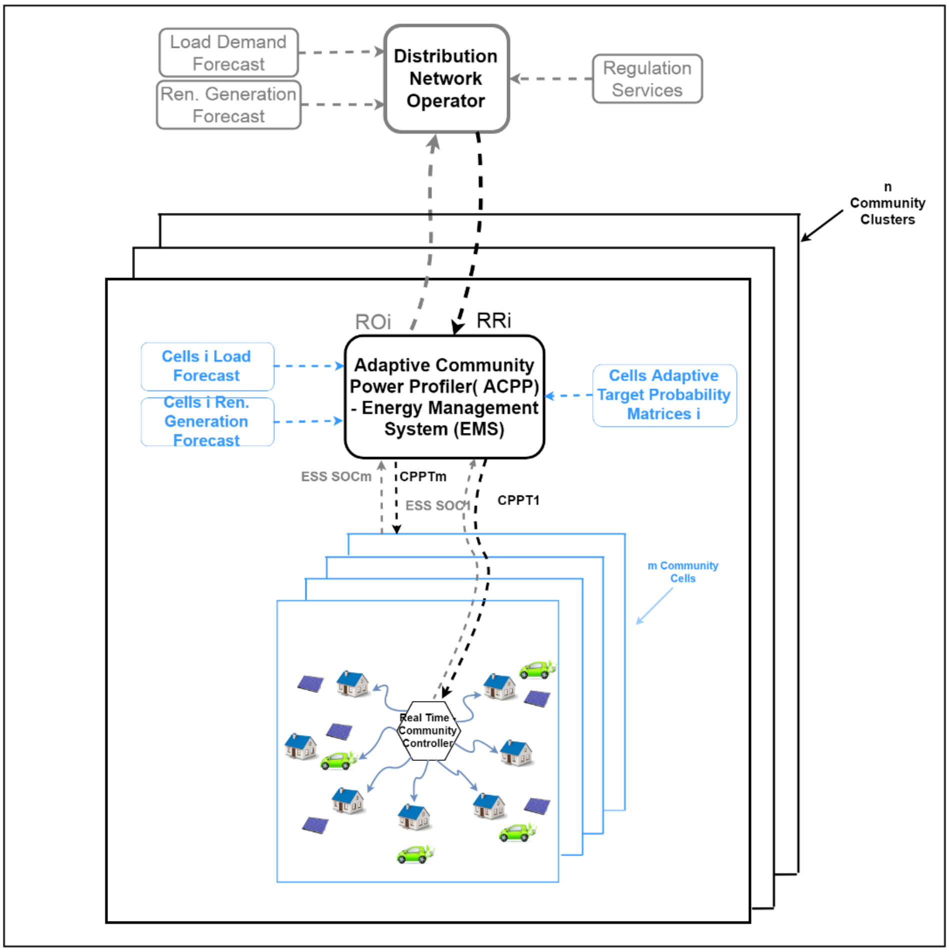

Fig 3.1 Proposed Hierarchical Control Framework

3.2.1 Community Cell

Each community cell is a low voltage, small, residential entity consisting of typical loads encountered in residential premises. Dominant residential loads are considered to be fridge-freezers, washing machines and ovens. Furthermore, distributed generation in the form of roof mounted photovoltaic (PV) systems and distributed Energy Storage Systems (ESS) are also assumed to be present. Finally Electric Vehicles (EVs), will play a predominant role in the community's power behaviour and are also considered.

The Electric Vehicles and dominant residential loads as well as the ES Systems (ESS) are controlled by a real time power flow controller, responsible to charge and discharge energy storage and adjust load demand, regulating the active power import accordingly. Furthermore, the real time controller is obligated to respect the power reference target created by the higher communities' controller the Adaptive Community Power Profiler –Energy Management System (ACPP-EMS) and presented in Figure 3.1 as Community Power Profiling Target (CPPTi).

In order for the community cell to be able to function properly, a communication infrastructure is required between the real time controller and all the controlled cell elements. In addition, besides the same level communication requirements of each community cell between controller and controlled subjects, requirements for cross-level communication between different levels of the control structure play a major role in the overall system behaviour. In the proposed hierarchical framework cross-level communications are kept to minimum to improve the robustness of the system, making the lower community level able to function even in periods of communication failure.

The real time controller at the community cell receives power targets every half hour (CPPTi) and transmits towards the higher ACPP-EMS, the community's aggregated ES systems SOC. The aggregated ESS SOC is the percentage of the distributed ES systems energy available compared to their aggregated capacity.

A number of different real time control strategies are available in the literature, as presented in Chapter 2, segregating into two main categories, centralised i.e MILP [22,24] or deterministic control algorithmic approaches as developed by Fazeli et.al. [25] and decentralised approaches commonly represented by multiagent systems [26]. For the realisation of the current work the lower level controller is assumed to be a centralised active power controller.

3.2.2 Community Cluster

In the proposed control framework, a "Community Cluster" is formed by a group of "Community Cells" which can either be fed from the same secondary transformer and low voltage feeders but can also in a more general approach, be anywhere without the requirement of electrical proximity. The Adaptive Communities Power Profiler-Energy Managements System (ACPP-EMS) as a controller is responsible to generate the power profile targets for each individual cell real time controller, which in turn is responsible for achieving the power target as stated in section 3.2.1.

The Community Power Profiler generates targets before the start of each day for each controlling community for the next twenty four (24) hour period in order to achieve its main objectives. These objectives are distinguished into two categories, local and global objectives. The most important of the local objectives are the maximisation of self-consumption of locally generated renewable energy, improved asset utilization by minimising network losses and asset over-loading and minimisation of energy import during peak demand periods and the following proportionate gain in economic benefit gain. The global objective of the ACPP-EMS controller is to become a part of the frequency regulation market. As part of the regulation market the ACPP-EMS controller when it is requested by the DNO, the highest level of the hierarchical framework, can take part in the regulation procedure.

No inner level communications exist in this part of the framework as it is clearly a control mechanism that is responsible to maximise the benefit for the controlling community both in economic and energy usage terms.

On the other hand, bilateral cross level communications are required both with the lower community level and the higher DNO level in order to achieve the best possible result. The bilateral communication with the highest, DNO level, is required as the ACPP-EMS goal is to become a part of the regulation market. According to the framework structure presented in Figure 3.1, when a request by the DNO is made (RR*i*), for regulation purposes, the ACPP-EMS controller will respond (RO*i*) with an offer based on what its controlled area can achieve to help the system return to normal operation boundaries.

If the proposed offer is accepted, then the ACPP-EMS controller will need to generate and publish new power targets for the controlled area “community cells” and at the same time change the scheduled future targets for the remaining part of the day. Since changes are made to the targets of the communities, this needs to be communicated, which leads to another job for the bilateral communication requirement between controller and the lower level real time community controller.

The intermediate level (ACPP-EMS) controllers communicates with each community every half hour to publish the power targets for each community as it was stated in the previous section. In addition if a request is made for regulation purposes during the day, the ACPP-EMS controller should be informed of the currently available energy reserves of the community in the form of SOC percentage and generate and publish the regulation target and the following targets after regulation period until the end of the 24 hours control period. The discussed communication requirements are presented in Figure 3.2.

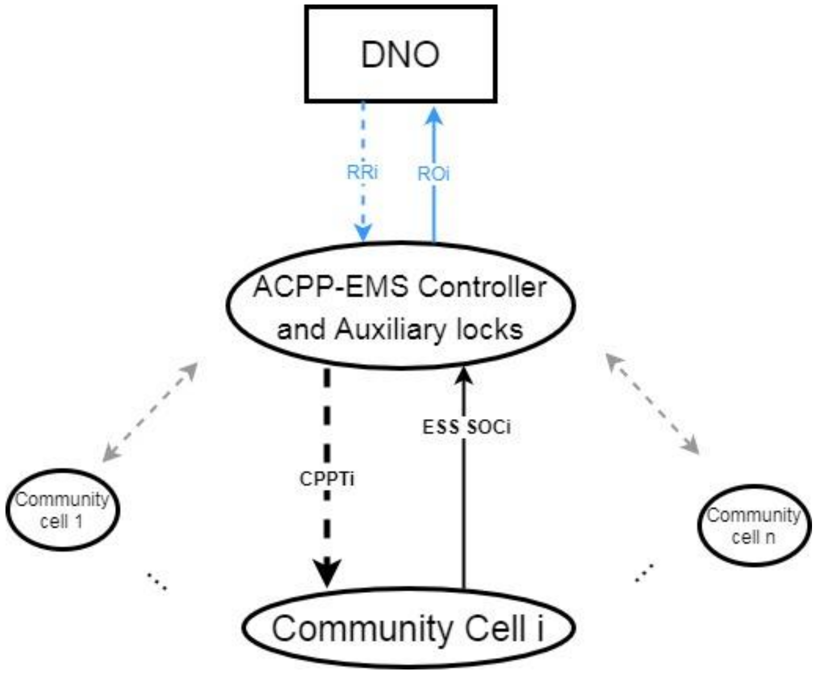

Fig 3.2 ACPP-EMS Communication Requirements

In order for the intermediate level ACPP-EMS controller to be able to fulfil its objectives, a clear picture of the expected load demand and renewable generation forecast for the scheduled control period should also be available. This requires that alongside the controller, prediction auxiliary blocks will be able to provide that information for a horizon of 24 hours into the future. However regardless of what forecasting technique is used and how advanced that techniques is, due the highly stochastic nature of PV generation and load demand, forecast errors are always present. According to [38] for a day ahead forecast of PV generation comparing Persistence, SARIMA and ANN techniques, the normalised root mean square average error for a year varies from 13.71-11.26%.

Due to unavoidable prediction errors, another block is also present as seen if Fig. 3.1 called the Adaptive Target Probability Matrix. This block is in turn is responsible for taking into account the expressed forecast uncertainties and help with target generation procedure. By implementing the ATPM, when a regulation request is negotiated penalties for not delivering the agreed energy adjustment can be avoided.

Details about the novel ACPFC-EMS controller's decision process and accompanied blocks are given in the chapter 5.

3.2.3 Distribution Network Operator (DNO)

The aim of the Distribution Network Operators is to maintain the stability of the entire distribution network providing an affordable, responsive, reliable and resilient network. According to [39] its primary role as a DNO will focus on the effective and efficient provision and balancing of network capacity.

Following the same line of thought in the proposed control framework the DNO is considered responsible for Regulation Requests (RR*i*), when it is required for balancing purposes, from the collaborating community clusters to adjust their behaviour according to the overall system stability requirements.

Of course, the proposed regulation service is not considered as the main or dominant balancing service but as a fast acting complementary service that can become a part of the of the total fast acting regulation sector bouquet. Accordingly, a new regulation market is proposed and described in the next section.

3.3 New Proposed Regulation service as part of the proposed framework

As part of the proposed framework a new regulation service is suggested which has fundamentally different characteristics than traditionally used regulatory services.

Traditional frequency response services [40] are distinguished between:

- The Dynamic Steady State/pre-fault response services that operate in the frequency range of 50Hz± 0.2Hz and are responsible for maintaining frequency as close to ideal 50Hz at all times without the occurrence of an actual network fault.
- The Transient State/post-fault services that operate in the frequency of 50±0,5Hz also called normal loss service which in turn is divided further into two more categories. The Primary Response (PR) that is responsible for arresting the frequency deviation before breaching the stated normal loss limits and the Secondary Response (SR) responsible for restoring the frequency operational limits.

In addition, traditional response survives are fixed capacity, fully dedicated providers that receive compensation during time periods that are not used and paid according to their energy capacity when they are used based on agreements signed between them and the frequency regulation organisation.

As part of this project, something new is proposed that can be located in the Transient State-Secondary response service area. According to the proposed scheme, each community cluster can act as a response provider when it is requested by the DNO. The capacity that each cluster has to offer might be fully flexible according to the how much the cluster can vary its energy profile or have a dedicated response service part and a flexible part which is dictated by what each cluster can achieve when it is requested.

After the request by the DNO is made, each community cluster is responsible for answering and publishing what it can achieve in terms active power import adjustment. All the clusters taking part in the scheme answer and make an offer to the DNO. If the offer gets accepted then each community cluster is responsible for accomplishing what was agreed with the DNO.

By following the proposed scheme, although each community cluster alone cannot compete with dedicated service providers in terms of capacity, can compete with them in numbers. If each DNO has a large number of community clusters that are willing to take part in the proposed market, then a large pool can be created that can provide a valuable and cheaper service than traditional regulation service providers.

In fact, by not having dedicated services the network operator is not:

- Obligated to pay compensation for standby services. Regulation service is only paid when it is used.
- Since regulation requests are sparse, any ESS in communities that are not on standby mode can be used by the communities to fulfil local objectives.
- By having that dual role on two different levels, small ESS have a greater economic benefit for their owners making them more affordable and economically viable.
- No capacity limitation (1 MW in current system) exist. Weaker microgrids can enter the market.

3.4 Conclusion

The hierarchical framework described in the previous section is the core idea that was used as a guideline, around which the different modelling techniques and algorithms where developed or adopted. The ACPFC-EMS as presented in Fig 3.1 is used to control small residential communities. That does not limit the usage of the proposed energy management system to only residential communities but can also be implemented to other types of similar scale loads as factories, schools, hotels that can be controlled by real time power balancing systems.

Besides the novel mid-level energy management system, the ACPP-EMS, accompanied lower level community residential loads, Electric Vehicle (EV) models, Battery Energy Storage Systems (BESS), photovoltaics (PVs) and lower level real time controllers where developed and adopted. All of the models mentioned above where realised in a MATLAB/Simulink environment and are presented in Chapter 4 and 5 in more detail.

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Chapter 4: Modelling Techniques and Data Sources

4.1 Introduction

In order for the proposed framework in general and the perceived ACPP-EMS in particular to be realised and tested at a later stage, a number of different models had to be implemented from the available literature and if not available, developed to use. In addition to the models, it was also necessary to obtain high quality data from real measurement systems to use as part of the framework for input signals.

Starting from the lower hierarchical level, according to the community structure presented in Fig3.1, the “community cell” should consist of a number sub-cell models that aggregated can create a current and near future residential community exemplar. Each cell is formed by:

- A number of individual dwellings which include all the main residential loads commonly encountered.
- Roof mounted photovoltaic systems as the most common residential distributed renewable generation system.
- A percentage of Electric Vehicle (EVs) used by the house occupants as the main transportation mean.
- Battery Energy Storage Systems (BESS) as the main energy storage for residential usage.
- The low-level Real Time Power Flow Controller, responsible for controlling the import power of the community with respect to the given power flow target.

The second/intermediate hierarchical level consisting of the Adaptive Community Power Profiler – Energy Management System will be presented separately, in Chapter 5 as the main contribution of this work.

Finally the third and highest hierarchical level will be presented in the form of regulation service requests towards the intermediate level, based on real system frequency data from the UK electrical network.

This chapter will present the models developed or adopted in the simulation procedure and the data and recourses for the acquired real data.

4.2 Residential Electricity Demand Model

4.2.1 Introduction

A residential electricity demand model able to generate realistic load profiles is critical in the delivery of detailed and high quality low voltage network distribution network studies. In United Kingdom according to ELEXON [41] eight generic load profile classes exist to represent the different type of customers on the network of which only two are considered domestic. These generic load profiles are given in half hour patterns and are calculated by using a weighted average procedure across the different population groups. Although the knowledge of the aggregated demand patterns of consumer groups is highly desirable for distribution network operators to study the evolution in time of power flow, it is completely insufficient for detailed low voltage studies on the distribution network.

The aim of a residential electricity demand model, for low voltage studies, is to create a high resolution electricity profiles for individual houses which can be replicated with some statistical variance. In the available literature a number of higher resolution models are available [42, 43, 44, 45, 46], created exactly to cover this need for higher detail residential load models. The available models separate into two major modelling approaches depending on the level of load detail each study considers important.

The top down modelling approach tackles the residential load demand modelling problem in terms of aggregated demand patterns of individual residential dwellings. High resolution stochastic models [42, 43] are generated using statistical and probability analysis techniques on recorded data from a small group of residential consumers load. In [42] the group patterns under study are represented trough a Beta probabilistic distribution at each time step. The aggregated time-coupled demand behaviour is estimated by using the distribution parameters varying from one step to the next. The parameters are calculated to provide the demand variation at two consecutive steps.

The bottom-up approach is more commonly used [44, 45, 46] as it is able to provide more detailed results at the lower level. By adopting a logic that starts from simulating individual household appliances demand and moves towards the total dwelling demand, it allows the representation of the residential usage at much higher detail. Statistical analysis and stochastic techniques are also used but at a much more fundamental level and using a much larger pool of data from social surveys e.g. the UK 2000 Time of Use Survey (TUS)[48].

In the bottom up approach, statistical analysis of appliance ownership and load demand of appliances in residential premises is used as the first step towards the creation of high detailed profiles. The individual appliance statistics in comparison to the behaviour profiles of the residence derived by Time of Use Surveys and in combination with stochastic methodologies e.g Markov chains and/or Monte Carlo create the second very important step. The third and final step is the combination of the above with outdoor environmental conditions and the incorporation of light profiles for the detailed generation of the high resolution stochastic profiles.

In this project the model proposed by Richardson [46] was used. The integrated high-resolution modelling of domestic electricity demand model is one of the most transparent and detailed representatives of the bottom up approach and will be presented in more detail in the next section.

4.2.2 I. Richardson: High-Resolution Modelling of Domestic Electricity Demand - Modelling Approach

The starting point for the creation of a Hi-Res Electricity demand model evolves around the concept of occupancy as a key driver of domestic energy demand [47]. As an example, an occupied dwelling at night is likely to have the lighting turned on. In an unoccupied dwelling this is highly unlikely.

As it can be observed in Fig 4.1 in a dwelling of four occupants, a clear correlation exists between active occupancy and power demand patterns. Of course, not all appliances are correlated with active occupancy with the most important example in terms of energy consumption being a fridge/freezer. During the time periods of no active occupancy only the cycling patterns of non-occupancy related appliances exist. However, in time periods of activity the power consumption is clearly higher.

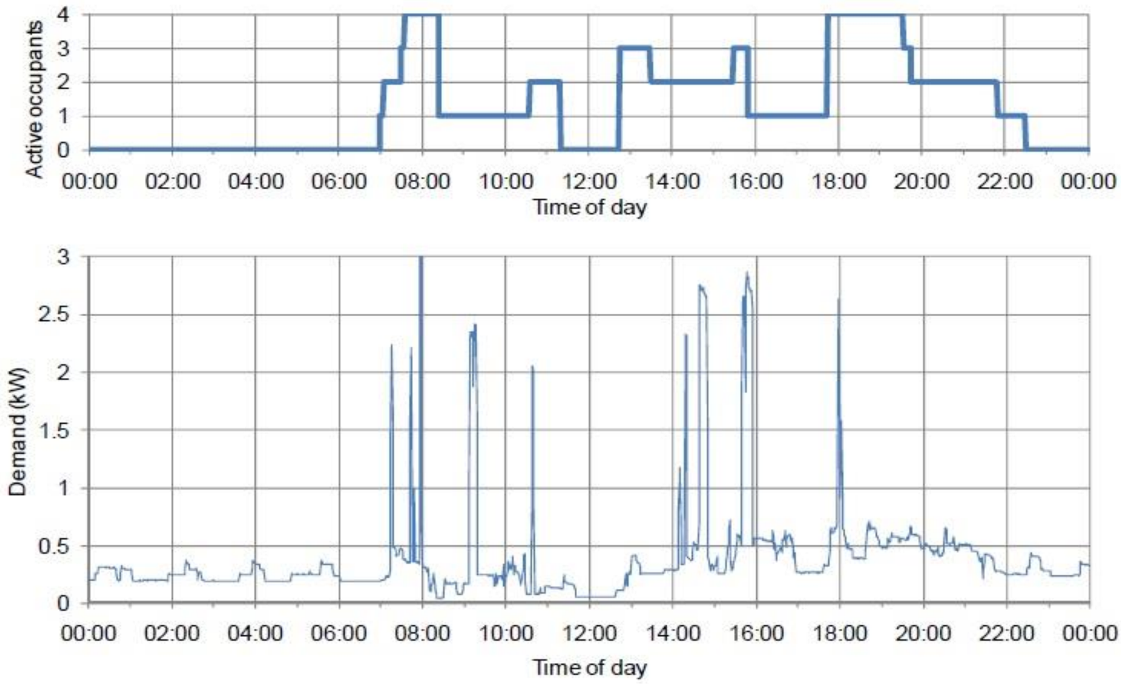


Fig 4.1 Patterns of active occupancy and electricity demand as part of the creation of High-Resolution Modelling of Domestic Electricity Demand model from captured data from the study of domestic electricity use in Loughborough area, East Midlands, UK

For the creation of synthetic occupancy data a first order Markov-Chain was created together with probability matrices of transition between states using as source data the UK 2000 Time of Use Survey (TUS) [48]. The two mentioned states are active or not active occupants and the probability matrices where created for each minute of a day, for weekdays and weekends respectively and for different household sizes (residents).

Using a random number generation and comparing them with the probabilities calculated in transition matrices for each time step of the day, the generation of individual (but with common characteristics) synthetic active occupancy patterns was achieved. In Figure 4.2 an occupancy synthetic pattern for a 3 occupant dwelling for a day is presented. As it can be observed, the occupants of the house are probably working individuals that are not home during the biggest part of the day. Due to that active occupancy can be noticed between

06:00 – 10:00 hrs before leaving for work and after 16:00 when the first occupants start to return home after work and until the end of the day.

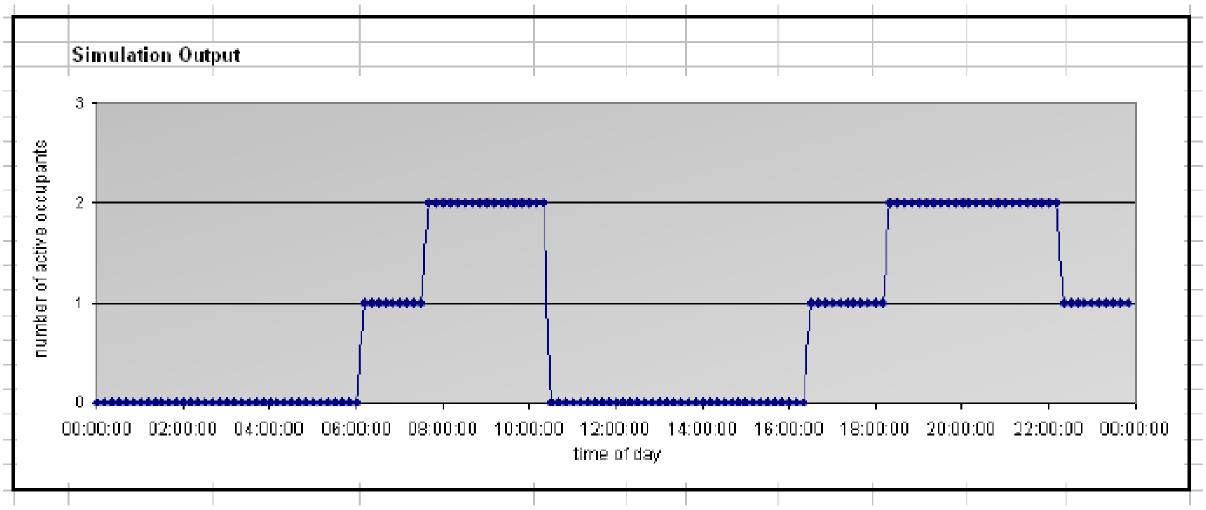


Fig 4.2 Active occupancy simulation output of 3 occupants dwelling for a day as part of the High-Resolution Modelling of Domestic Electricity Demand model.

As stated, using the active occupancy as the key input for a dwelling`s overall power demand the power model is divided into two smaller sub-problems:

- the domestic lighting usage and power demand.
- the electric appliance usage and power demand.

4.2.2.1 Domestic Lighting

Starting from the domestic lighting sub-problem [49] a number of influences (ignoring active occupancy), were identified as the most important for the modelling of the lighting load demand. Firstly the natural lighting level. Clearly people use lighting after the natural light fades away. Secondly the majority of the lighting devices are not used only by one occupant but a larger number of actives occupants may share the same lighting unit. Thirdly a different number of lighting unit technologies exist (e.g halogen lights, fluorescent lights etc.) and are installed at different parts of a residential unit. Finally different lighting units at parts of the dwelling are used more often than others. Described by the term "relative usage of lighting units" a weighting factor is used to exactly take into consideration the fact that lighting units in commonly used areas e.g. the kitchen are used more often than a storage room light. All of the above are presented in Fig 4.3.

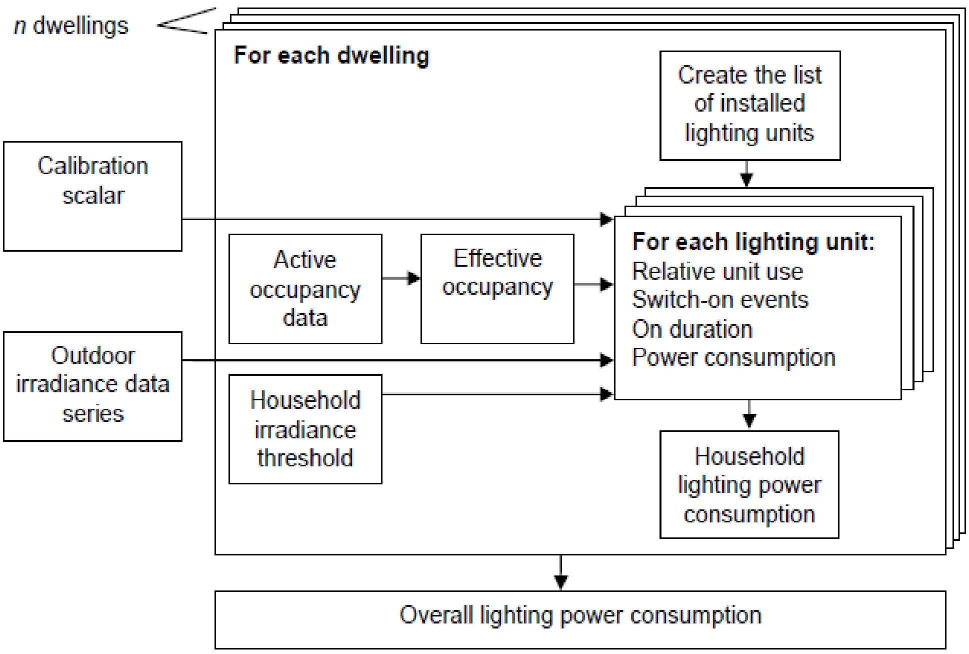


Fig 4.3 Outline structure of lighting model as part of the High-Resolution Modelling of Domestic Electricity Demand model.

The calibration scalar shown in Fig 4.3 is a number that (as justified by the author) was determined after running the simulation multiple time for a large number (100) of dwellings for a year in order that the output lighting demand would be equal to the average lighting demand of 715 kWh/year. Furthermore, the active occupancy is used in conjunction with "effective occupancy" parameter which is a scaling factor that takes into account the fact that a number of occupants can share the same lighting unit.

By combining all the above and after a list of installed lighting units is created for each simulated dwelling, for each lighting unit available, the likelihood of a switch on event is given by the factors presented in Fig. 4.4.

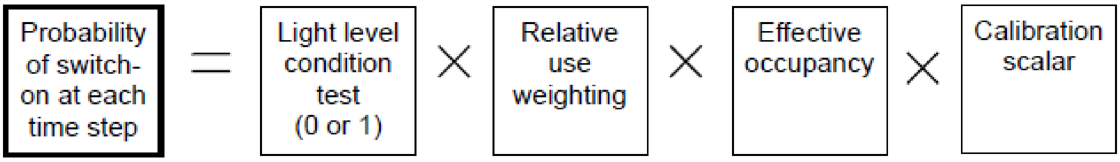


Fig 4.4 Calculation of switch on probability of lighting units as part of the High-Resolution Modelling of Domestic Electricity Demand model.

This gives a general picture of how the lighting power demand sub-problem was solved as part of the Domestic Electricity model that was chosen as the most detailed and transparent of those available in the literature.

4.2.2.2 Domestic Electricity Appliances

Following a similar logic to the lighting sub-problem the major influences for the usage of domestic electricity appliances where also identified by the author and taken into consideration [50]. Of course, again active occupancy is the most important influence and the starting key for everything. The first of the other important influences is the fact a lot of domestic appliances are used by more than one person. A typical example of this is the oven when used for cooking. If one person is active and the oven is turned on and a second occupant enters the room that does not mean that the load demand usage will double because the active occupancy also doubled. That is described as sharing of appliances. Secondly a number of different appliances can be installed in a dwelling and in some situations in higher numbers than just a single device e.g TVs. Thirdly different devices have different probabilities of being used at different times of the day e.g if its weekday or weekend and at different active occupant levels in the dwelling. The structure of the electricity demand model is given in Fig. 4.5.

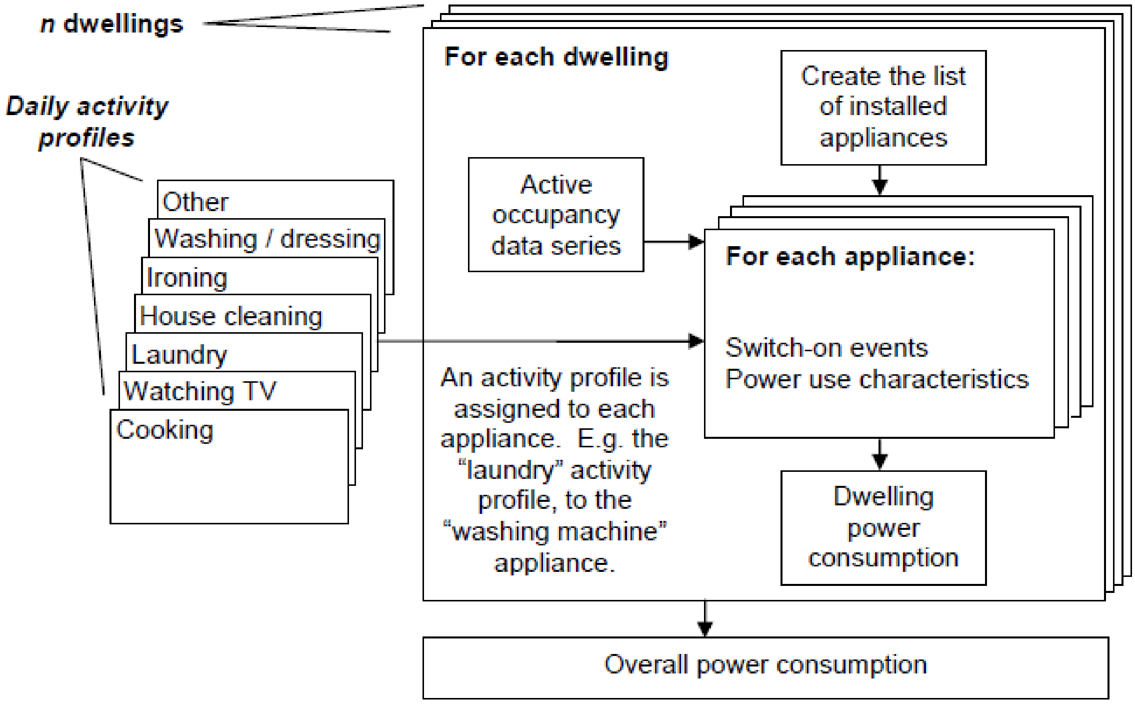


Fig. 4.5 Structure of the domestic electricity appliance demand model as part of the High-Resolution Modelling of Domestic Electricity Demand model.

The set of daily active profiles on the left of the Fig 4.5 seen in the domestic appliance structure is used in [50] to take into account the points described in the previous paragraph. In spite of the fact that active occupancy can be at similar levels at different times of the day, the probability of a person cooking for example, although is always present, changes if it is around supper time or not. Furthermore, cooking probabilities also change depending if its weekday or weekend.

The installed appliance list is also unique for each dwelling created and is allocated from a list of 33 major appliances commonly used. Using the available statistics on appliance ownership and following a first order Markov technique a stochastic list of installed appliances is created for each individual dwelling.

Of course, for each installed appliance a process should be followed in order to determine the probability of an appliance being turned on. The switch-on event procedure is given in Fig 4.6

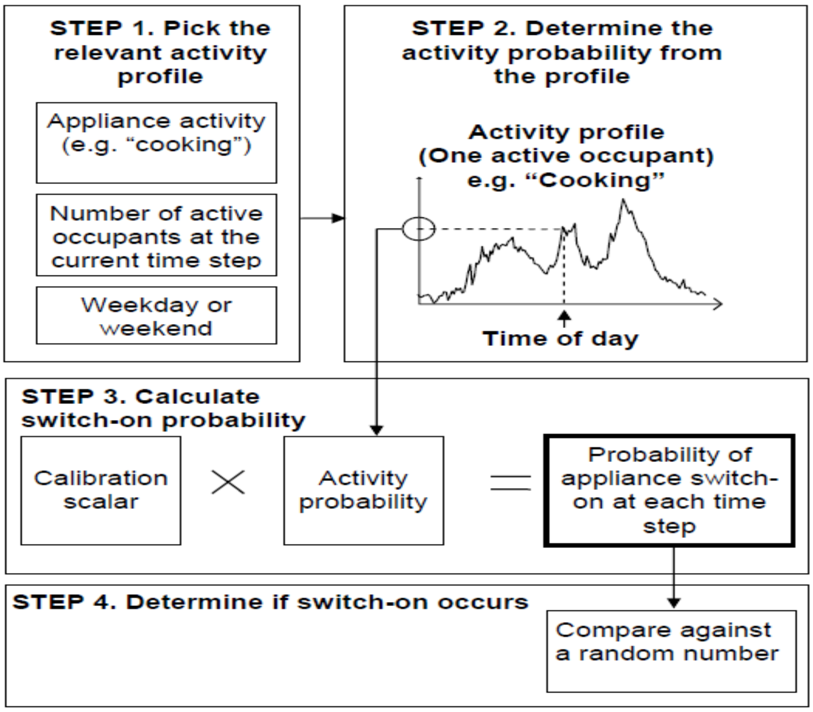


Fig. 4.6 Switch on appliance events of the domestic electricity appliance demand model as part of the High-Resolution Modelling of Domestic Electricity Demand model.

As seen in the Figure 4.6, the procedure of determining if an appliance is turned on consists of four steps. Firstly, find the correct active occupancy level from the activity profile and day of the week. Secondly locate the correct activity profile for that specific appliance. Thirdly multiply the probability from the activity profile with a calibration scalar and finally compare the overall probability with a random number to determine if the appliance is turned on at that time step.

The allocated calibration scalar is a number that was calculated in [50] such that each individual device will not run more often that it should. The mean number of times an individual device should run for a year is statistically known. The switch on event probability should be calibrated in order to match the statistically predicted number of usage in a year.

4.2.3 Conclusion

The presented model proposed by Richardson [46] was used to generate the synthetic power demand data for the dwellings used in the low level "community cell" part of the proposed hierarchical control framework. The model was used as stated due to it`s clarity and transparency but also due to its ability to generate 1-minute electricity consumption data for an individual houses, making the creation of difference size community cells very easy. Finally, due to the fact that the model is adopting a logic that starts from simulating individual household appliances demand and moves towards the total dwelling demand, it allows the future introduction of demand side management capabilities at a future stage at the low cell level real time controller.

4.3 Electric Vehicle Model Development

4.3.1 Introduction

According to available literature, when electric vehicles become the main means of everyday transportation and a high penetration is achieved, they will become one of the most significant residential loads due to their charging power and overall energy request, and will have a major impact [51, 52, 53] on the low voltage electricity grid.

A novel approach to develope a high resolution EV model, following the bottom up logic will be presented in the next section and will be used as part of the community`s cell loads during the testing of the ACPP-EMS. Existing EV models as presented in the literature [54, 55, 56] cannot realistically quantify the electric vehicles availability through the day and the charging power requirements but are based on assumptions without using a justified statistical method.

The presented model in [54] selects the start of the charging period randomly from four predetermined charging period during the day and charges until the vehicle is fully charged. Another model using a similar approach presented in [55], randomly quantifies the SOC at the start of charging time and charging time based on probability distribution functions that are not based on any real transportation survey data. Finally, a model presented in [56] also uses probability distributions to randomly allocate the time of departure, location and next activity for every EV model/agent as well as distance driven and energy consumed but the statistical method used to acquire the stated variables is not provided.

4.3.2 Model Development

In this section the construction of a novel high resolution EV model approach will be presented. The model simulates the use of Electric Vehicles from individual drivers, by using a combination of drivers car usage behaviour based on statistical analysis of available data and the consumption and charging demand given by the manufacturer specification data of a well know currently available all electric plugged-in EV [59].

4.3.2.1 Features of the model

4.3.2.1.1 EV Usage Consumption and Charging Demand

One of the newest and widely available models of a fully electric plugged-in EV was chosen for the specifications guide of the EV model constructed. Charging time, load demand and consumption specifications for the EV model when in use is based on the Volkswagen e-up all electric vehicle.

4.3.2.1.2 EV usage profile

The EV usage profile is the key around which the EV model was built. The usage profile of vehicles was calculated from analysing the available data from the National Travel Survey (NTS) 2014 [56]. Although the data available in the survey are for the usage of normal petrol vehicles, the assumption was made that although the technology of vehicles might change people will continue using them identically to fulfil their everyday needs. It is assumed that battery technology will develop to allow comparable distance ranges with petrol cars.

4.3.2.1.3 Relative distance travelled

The relative distance travelled is the difference in distance travelled by vehicles although they used for the same time period. For example, two different vehicles can be in use for the same amount of time. The first one was used in the motorway for most of its trip and the second one was used mostly in smaller urban roads. In reality the first vehicle will have travelled much bigger distances than the second, the model represents this by using a distance probability matrix created from the NTS raw data.

4.3.2.1.4 Temporal resolution

Since the EV model will be used in common with the residential electricity demand model at the low "community cell" level, the model will generate data at one-minute resolution. Of course, the model is designed in such way to be able to vary that resolution if required.

4.3.2.2 Construction of the model

To create each EVs the overall power demand profile a number of steps must be followed. The steps required are presented in Figure 4.7

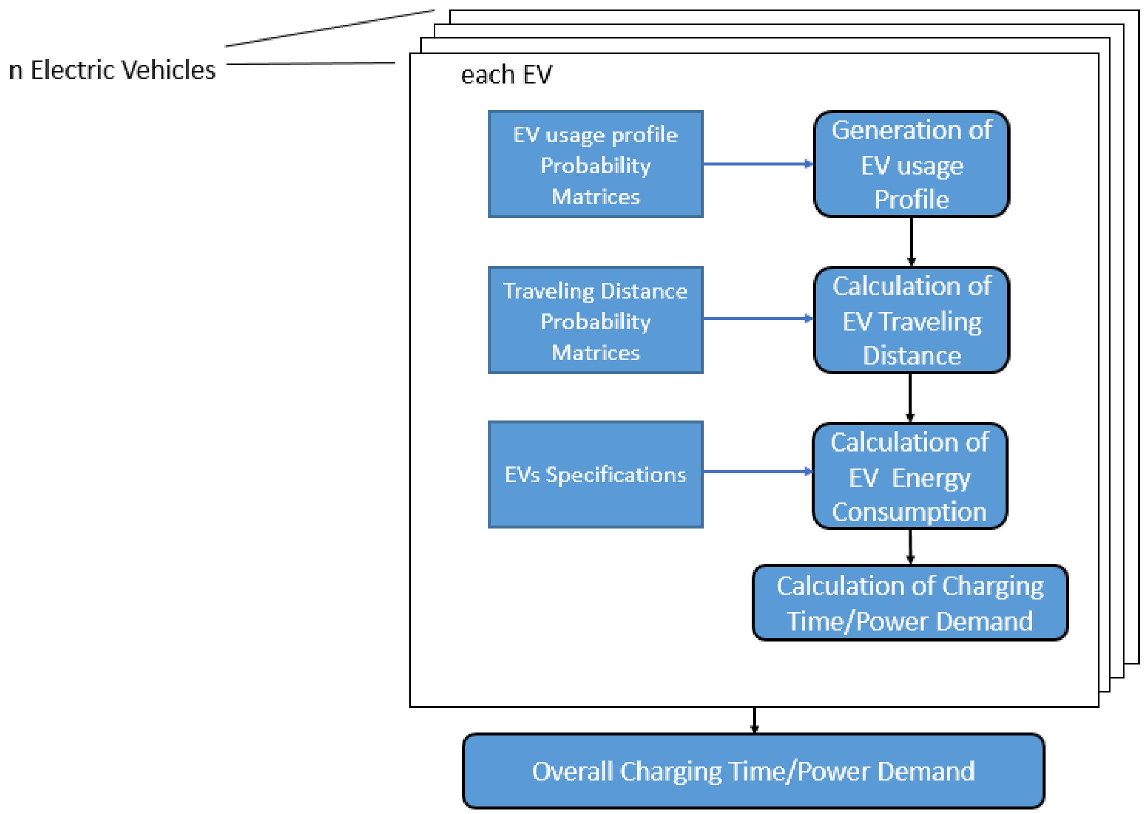


Fig 4.7 Electric Vehicle model architecture

The followed procedure for each EV model consists of four distinct steps as presented in Figure 4.17:

- The Generation of the EV usage profile.
- The calculation of the relative travelled distance based on the previously generated usage profile.
- The calculation of the energy consumed during the travelling.
- And finally, based on the previously consumed energy the calculation of the Power demand and time period needed for charging the vehicle

To the left of the Figure 4.7 the inputs for the calculation for each step of the modelling procedure is given by the blue rectangle boxes. At each step a stochastic approach is used to determine if an electric vehicle is in use or not, what was the distance travelled and the energy consumption. By adding the charging demand for every simulated vehicle at each time step the EVs power profile is generated. The overall simulated EV fleet charging power demand is the aggregation of the power profile from each EV.

4.3.2.2.1 Generation of EV usage Profile model

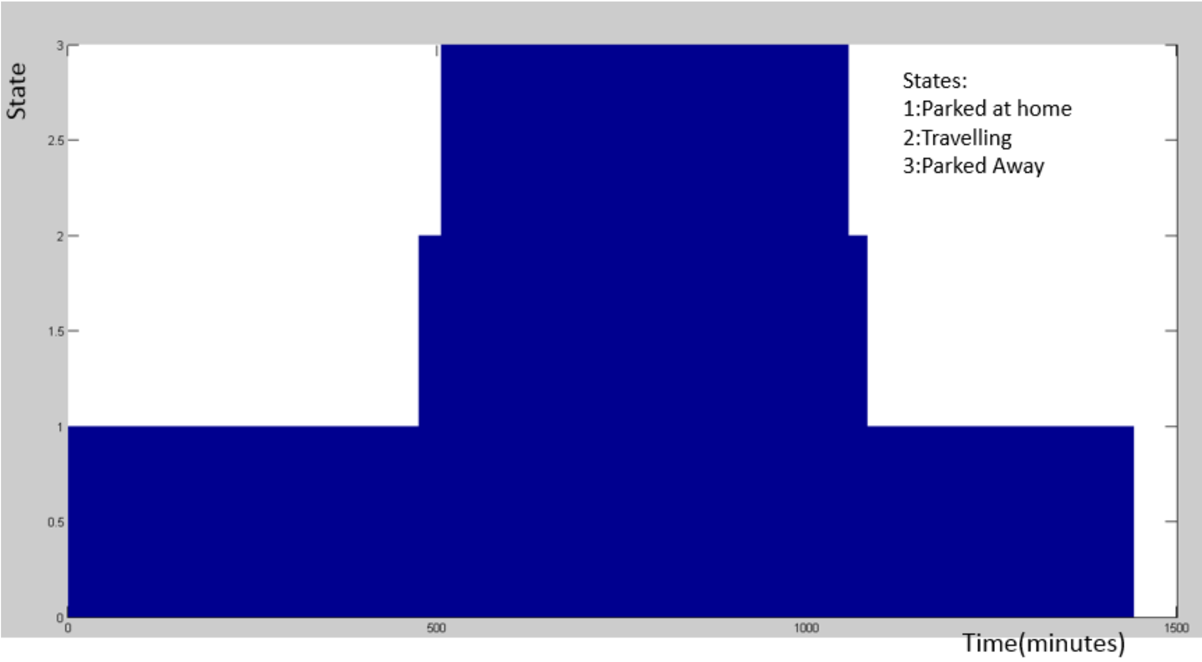
The data available from the National Travel Survey (NTS) 2014 [57] were used as the source data for the construction of a model of EV usage profile. During the survey a 7-day travel diary was completed for each individual taking part in the survey including information about everyday transportation in a special “trips” section.

The trip section available including each individual’s information was also 7 days. The most important information for the realisation of the EVs usage profile model for each individual taking the trip were the day of the trip, the means of transportation used (e.g. privately own vehicle, type of public transportation, etc.), origin and destination of the trip, starting and finishing time of the trip, distance of the trip and actual time of the trip. After filtering the raw data to maintain only private vehicle individual drivers, a pool of 5000-6000 individuals was created with clear –full day diary for each day of the week.

The raw data where manipulated even further, separated into individual days and the number of trips was found per day for each individual driver in terms of start/finish time and of course origin/destination. In order to reduce the origin/destination combinations and simplify the analysis, the assumption that the actual destinations away from home is not considered important was made. The stated assumption was made since no matter what the actual destinations away from home is, that does not affect the consumption of the EV and consequently the EV usage profile model itself. If a car is parked at the workplace parking area or the supermarket parking area that does not change the fact that the car is away from home. Based on the stated assumption it was assumed that an individual car/driver can only be found in three 3 distinct states:

- Parked Home.
- Travelling/In use.
- Parked away from Home.

An example of a real car usage profile following the three distinct states logic for an individual driver for one day according to the NTS 2014 survey diary data is presented in Figure 4.8.



State	1	1	...	1	2	...	2	3	...	3	2	...	2	1	1	...	1
Time(min)	1	2	...	474	475	...	504	505	...	1054	1055	...	1080	1081	1082	...	1440

Fig. 4.8 Real car usage profile chart and matrix of an individual driver for one day (Monday) according to the NTS 2014 survey diary.

To construct an EV usage profile model able to generate realistic synthetic data with identical statistical characteristics to the raw available data from the NTS 2014, a first order Markov-Chain [58] technique was used.

According to the Markov-chain technique a Transition Probability Matrix (TPM) should be created, that contains the probability of the transition from one state to the next for every time step of the day according to the model resolution. The probability calculation is of course based on the source data. An example of a TPM is given in Table. 1. The presented TPM contains the probability of moving from one state to the next for minute 754 to minute 755 of a weekday. Consequently, to cover a whole day with a resolution of one-minute 1439 TPMs are needed.

Current State/Next State	1	2	3
1	0.999861	0.000139	0
2	0.116331	0.880686	0.002983
3	0	0.001814	0.998186

X 1439

Table 1. Transition Probability Matrix from minute 754 to minute 755 on a weekday.

The construction of the TPM involves the calculation of the likelihood of a car moving from one state to the next (be Parked at home/In use/Parked away from home) at a certain time step of the day. All the possible states are three so in total nine transition probabilities exist. For example to calculate the probability of a car which is parked at home (state 1) moving to other states, all the individual cars that are in state 1 at the 754 minute of the day must be found. Secondly the state of the same cars at the next minute should be determined and put under the correct state column. The probability of changing a state is given by dividing the number cars of each individual state at minute 755 by the total number of cars with the same starting state. The matrix to construct the TPM in Table 1 is illustrated in Table 2.

	Number of occurrences			Total Number of Same starting state	TPM		
Current State/Next State	1	2	3				
1	2106	4	0	2106+4+0=2110	2106/2110	4/2110	0/2110
2	1	406	25	1+406+25=432	1/432	406/432	25/432
3	0	23	2604	0+23+2604=2627	0/2627	23/2627	26047/2627

Table 2. Construction of a Transition Probability Matrix from minute 754 to minute 755 on a weekday.

In order to represent a whole day 1439 different 3X3 TPM matrices are needed at each transition from one minute to next due to the fact that probabilities of changing state change throughout the day. Furthermore, since it is evident that probabilities are going to be different between weekdays and weekends, the described procedure was repeated for weekends. The total number of required matrices is 1439 for weekdays and 1439 for weekends totalling to 2878 of (3x3) matrices.

Although all the required matrices to generate the synthetic EV usage profile are now ready, the issue of what should be the state of each generated EV at the start of the simulation process has not been answered. The start time of the simulation process is considered to be Sunday to Monday 00:00 at night. Following the Markov technique as before, all the available information were gathered from the survey diaries to construct a Start State Probability Matrix (SSPM).

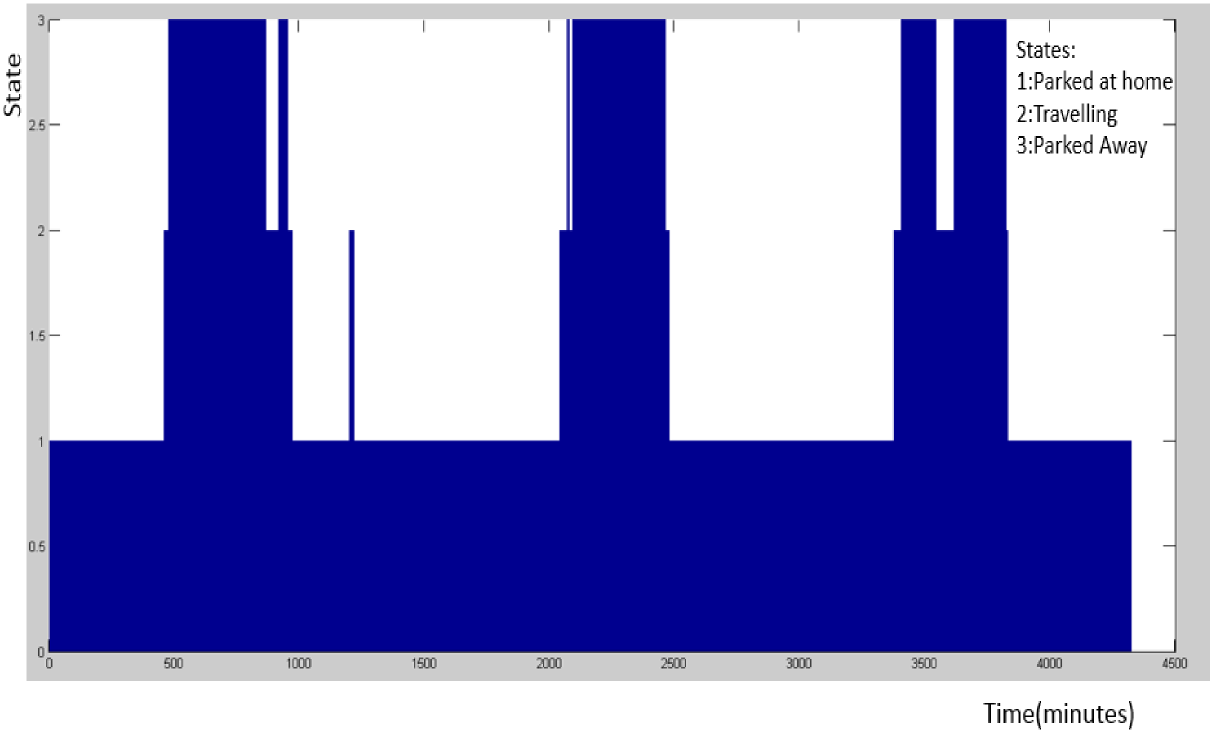
Starting State	Number of Drivers in Each State	Total Number of Individual Drivers M0nday	Start State Probability Matrix
1	4877		4877/5256=0.9279
2	1		1/5256=0.0001512
3	378	5256	378/5256=0.0719

Table 3. Construction of a Start State Probability Matrix.

As illustrated in Table 3, the state of all individual drivers from the raw NTS survey data was identified at the designated start time. The probability of an EV being at one of the three states was calculated by dividing the total number of cars at each individual state by the total number of cars for all states. The start state can be stochastically determined by comparing a random number with the probability of an EV being at a certain state.

Once the start state is known, the generation of individual EV usage profiles can begin by using the first order Markov-chain Monte Carlo technique and the Transition Probability Matrices for weekdays (TPM-WD) and weekends (TPM-WE) to determine each future state at the next step. A random number between 0 and 1 is generated and compared with the cumulative transition probability at every time step. If the state transition probability is higher than the random number then a transition occurs, if not the state remains the same during that time step.

A generated EV car usage profile for three weekdays for an individual driver is presented in Fig. 4.9. As can be seen the vehicle, as expected for weekdays, is mostly active in the morning and evening for traveling to work and back. On the first day a very short use of the car later in the evening might suggest a small vehicle usage for personal reasons while during the third day a small usage of the car during lunch break hours might also suggest the use of the vehicle for personal needs.



Fiq. 4.9 Generated Synthetic EV usage profile of an individual driver for three days.

4.3.2.2.2 Calculation of EV relative travelled distance

Having generated the EV usage profile in the previous section, the information about the time period an EV was in use can be acquired in detail, but no information about the actual distance the vehicle covered during the time it was in use exists. As it was mentioned earlier two identical vehicles can be in use for the same amount of time but cover different distances. The first might be driven in an urban area and the second one for most of the time on a motorway. The distance covered and consequently the consumption of the two vehicles is completely different.

The problem described is highly stochastic and requires a similar approach as the EV usage profile. Following again the Markov-chain technique, distance probability matrices should be constructed displaying identical characteristics to the NTS survey time [57] of use and distance travelled with the highest possible clarity. In order to achieve this, all the available 113522 individual trips from the survey diaries where found and for each individual trip the total trip time (minutes) and distance (miles) were taken into account.

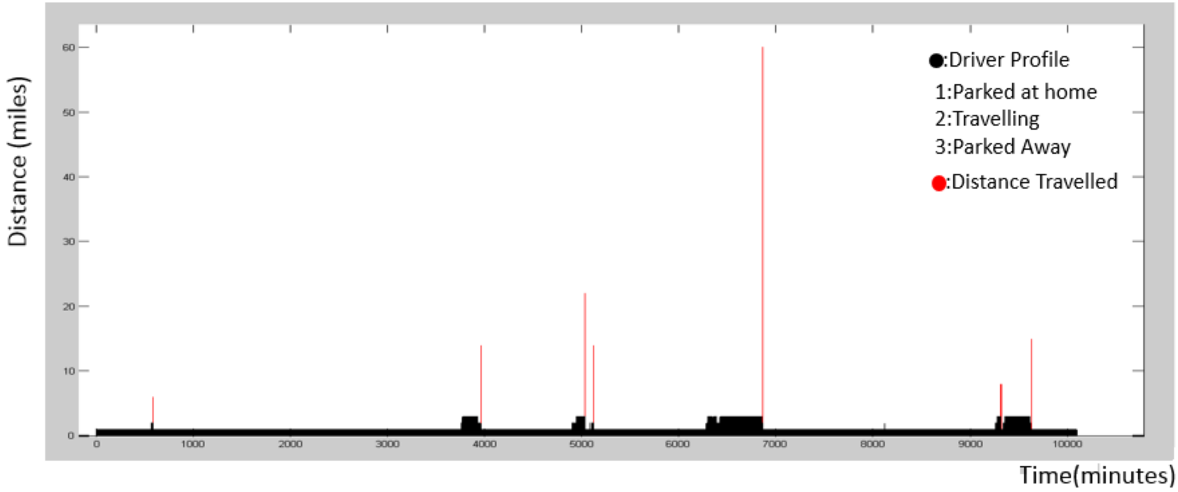
The distance travelled probability matrix represents the likelihood of a car travelling a certain distance while it was used for a specific amount of time. The construction of the matrix can be seen in Table 4. The time usage data were divided into five minute bins, in order to group together vehicles that have covered similar distances without losing information. 48 possible time bins exist base on the available data, starting from a time of car usage between zero to five minutes and going up to four hours of car usage.

Time Bin/Distance (miles)	Number of occurrences				Total Number of Same starting state	Distance Probability Matrix			
	1	2	...	613					
1	11214	5323	...	0	11214+5323+...=17748	11214/11748	5323/17748	...	0/17748
:	...	...	...	...	...	...	...	...	...
49	0	3	...	0	0+3+...=185	0/185	3/185	...	0/185

Table 4. Construction of the Travelled Distance Probability Matrix.

The distance covered is given in the columns section and can be between one to 613 (biggest recorded distance according to [57]) miles. To calculate the probability of a car which has travelled for a certain amount of time to have covered a certain distance, all the individual cars trips that are in the same time bin must be located. Secondly the distance for each of these cars travelled needs to be also located and placed under the correct distance column. The probability of a car covering a certain distance is given by dividing the number cars for each individual distance by the total number of cars in the same bin.

Once the time travelled is known the stochastic calculation of the distance can begin by using the first order Markov-chain Monte Carlo technique and the Distance Travelled Probability Matrices (DTPM). A random number between 0 and 1 is generated and compared with the cumulative distance probability at every distance between one to 613 miles. If the distance probability is higher than the random number, that is assumed to be the distance the car travelled. A generated usage profile for seven days and the distance travelled based on that profile is given in Fig 4.10. As it can be seen in the figure this is the profile of an occasional vehicle user that uses the car in non-fixed hours without standard weekday patterns. In Figure 4.10 the distance travelled is presented with a red line



Fiq. 4.10 Generated Synthetic EV usage profile for seven days of an individual driver and the distanced travelled when the car was used.

4.3.2.2.3 Calculation of Energy consumed- Charging time and Power demand

The final step of the EV model is the calculation of the energy consumption of the vehicle during the time it was used and consequently the charge time and power. For the calculation of the consumption of an EV one of the newest and widely available models of a fully electric plugged-in EV was chosen as the specifications guide for the EV model constructed.

Based on the Volkswagen e-up all electric vehicle specification datasheet given by the manufacturer [59] the combined consumption of the vehicle is 11,7 kWh for a range of 62 miles, therefore a combined constant consumption of 0.18871 kWh per mile. Relying on the previously calculated consumption and since at the previous step of the EV model the travelled distance in miles was calculated, the consumption of a modelled EV is given as follow:

$$E_{cons.i} = D_{ti} * 0.18871 \quad (4.1)$$

E_{cons} is the consumed energy during a trip for an ith EV, $D_t i$ is the trip distance in miles for that EV.

Since the energy consumed during a trip is known, the final peace of the puzzle is the calculation of the required charging time. Making the assumption that an EV can only be charged when parked at home (state 1) and the charging point is a regular domestic electric socket with a charging power of 3 KW, the charging period can be calculated in eq. 4.2:

$$T_{char.i} = \frac{E_{cons.i}}{3} \quad (4.2)$$

$T_{char.i}$ is the charging time required to replenish the energy used during the last time the ith EV was used. Each EV is charged after it is used when it returns in state 1, for a time period equal to $T_{char.i}$ and requires 3KW of power during the whole charging period.

4.3.3 Conclusion

The developed model follows a transparent methodology described in detail, able to provide high-resolution modelling of EVs. Clear statistical analysis and modelling techniques based on real car usage data from the NTS 2014 survey were used during the model development in order to generate realistic synthetic EV power usage data. The EV model presented in this section was created and used at the “Community Cluster” level for the development and testing of the ACPP-EMS.

4.4 Battery Energy Storage System Model

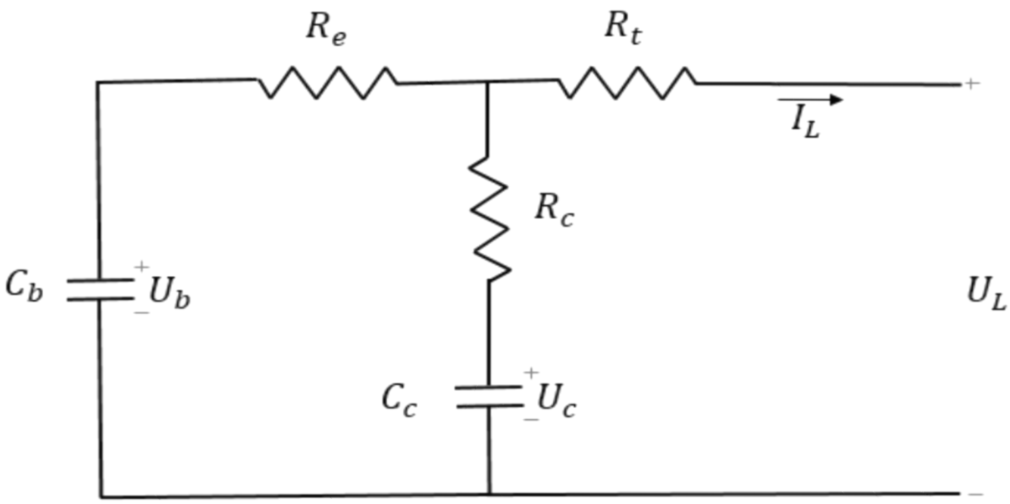
4.4.1 Introduction

An important part of the low "community cell" level hierarchical structure as it is proposed in chapter 3 are the local energy storage systems. Typical examples of privately owned and currently available residential ESS are the Tesla Powerwall, the Moixa Smart Battery system and the Sharp energy solution battery system [9, 10, 11]. Obviously the mentioned systems, as are the vast majority of similar systems, are Battery ESS (BESS) and very often combined with solar panels for the utilisation of surplus locally produced energy. A simplistic but accurate and transparent model of a BESS system model, able to be used in conjunction with the previously adopted and developed models is presented in the next section. This model was implemented in [60] as a model of electric vehicles battery pack. The model is based on the Resistor-Capacitor (RC) equivalent circuit by the SAFT Battery Company [61] and will be explained in more detail in the next section.

4.4.2 Lithium Ion Battery Model

The model presented is based on the equivalent RC model of a Lithium-Ion Battery. The model as stated was designed by the SAFT Company and was evaluated in [61] in comparison with other available equivalent circuits. According to the evaluation results the average State of Charge (SOC) estimating error after six consecutive test cycles was equivalent to 0.0167% compared to real experimental results and the average Voltage error equivalent to 0.2336 Volts. Consequently, the RC equivalent circuit can provide the basis for a transparent, easy to implement and accurate model of a Lithium-Ion Battery.

The model as seen in Fig. 4.11 consists of two capacitors, a small C_c capacitor which represents the surface effects of the battery and a large C_b capacitor which represents the actual energy storing capability of the battery. The three resistors R_t, R_e, R_c are called the "terminal", the "end" and the "capacitor" resistor respectively.



Fiq. 4.11 Schematic Diagram of RC model

U_b and U_c are the voltages across the C_b and C_c capacitors respectively and the $I_L$and U_L the output current and voltage at the terminals of the battery. The electrical behaviour of the model is described by the state space equations (4.1) and (4.2)

$$\begin{bmatrix} U_b \\ U_c \end{bmatrix} = \begin{bmatrix} \frac{-1}{C_b(R_e+R_c)} & \frac{1}{C_b(R_e+R_c)} \\ \frac{1}{C_c(R_e+R_c)} & \frac{-1}{C_b(R_e+R_c)} \end{bmatrix} \begin{bmatrix} U_b \\ U_c \end{bmatrix} + \begin{bmatrix} \frac{-R_c}{C_b(R_e+R_c)} \\ \frac{-R_e}{C_b(R_e+R_c)} \end{bmatrix} [I_L] \quad (4.1)$$

$$[\mathrm{U_L}] = \begin{bmatrix} \frac{\mathrm{R_c}}{(R_e+R_c)} & \frac{\mathrm{R_e}}{(R_e+R_c)} \end{bmatrix} \begin{bmatrix} U_b \\ U_c \end{bmatrix} + \begin{bmatrix} -R_t & -\frac{\mathrm{R_e} R_c}{(R_e+R_c)} \end{bmatrix} [I_L] \quad (4.2)$$

For the equivalent circuit parameters, the values shown in Table 5 and obtained from [62] were used. The stated values were used to simulate a 6Ah lithium ion cell. To simulate the desired BESS size, the necessary number of cells should be connected in a series/parallel combination.

Parameter	Value
R_e	1.1 mΩ
R_c	0.4 mΩ
R_t	1.2 mΩ
C_b	82 kF
C_c	4.074 kF

Table 5. Equivalent RC circuit Values

Finally, in order to deploy the battery pack, the evaluation of the charging or discharging current needs to be calculated at every time step. To accomplish the above, the approached followed in [63] was employed. According to that approach the charging current (I_c) can be calculated by (4.3).

$$\mathrm{I_c} = \frac{\mathrm{P_{charging}}}{\mathrm{V_B} * \varepsilon_c * \varepsilon_\iota} \quad (4.3)$$

Where $\mathrm{P_{charging}}$ the charging is request, ε_c and ε_ι are the controller and inverter efficiencies and V_B is the voltage across the battery pack. The efficiencies are considered constant and equal to 0.98 and 0.978 for simplicity.

The new State of Charge (SOC) of the battery (per unit or %) is calculated at every time step based on the previous know SOC_{t-1} and the change in the state of charge Δ_{SOC} during the time step as seen in (4.4). The Δ_{SOC} can be in turn calculated by using (4.5) where the Δ_t is the time step length, Co is the capacity of the battery.

$$SOC_t = SOC_{t-1} + \Delta_{SOC} \quad (4.4)$$

$$\Delta_{SOC} = \frac{I_c * \Delta_t}{C_o} \quad (4.5)$$

The Battery charger is also responsible to ensure that the maximum and minimum SOC limits are respected during the battery pack use. In this situation the limits chosen were 95% maximum and 25% minimum SOC during charging and discharging respectively.

4.5 Low Level Real Time Power Flow Controller

4.5.1 Introduction

As part of the lower "community cell" level a simple but resilient and effective real time power flow controller needs to be developed. The real time community controller should be able to cooperate with the higher hierarchical level, following the given community power target.

Although a real time controller can become very complex, especially by deploying Demand Side Management (DSM) strategies, this is out of the scope of this project. Based on the hypothesis that energy storage systems are the dominant flexible resource in any community energy system, DSM techniques can be initially neglected. However it should be noted that EV charging is considered as a disruptive influence on future distribution systems and a charginging management function is inclucted at the community cell real time controller.

A number of more complex real time controller techniques and approaches are available in the literature [64, 65, 66, 67] and can be implemented as part of future research and performance comparisons, which can incorporate DSM and other resources.

Another assumption used as this stage is that all the smaller privately owned house battery systems that are scattered around a community can, without the loss of generality, be considered as it is perceived by a higher level entity as one centralised community BESS with a capacity equal to the aggregated capacity of each individual house battery energy system

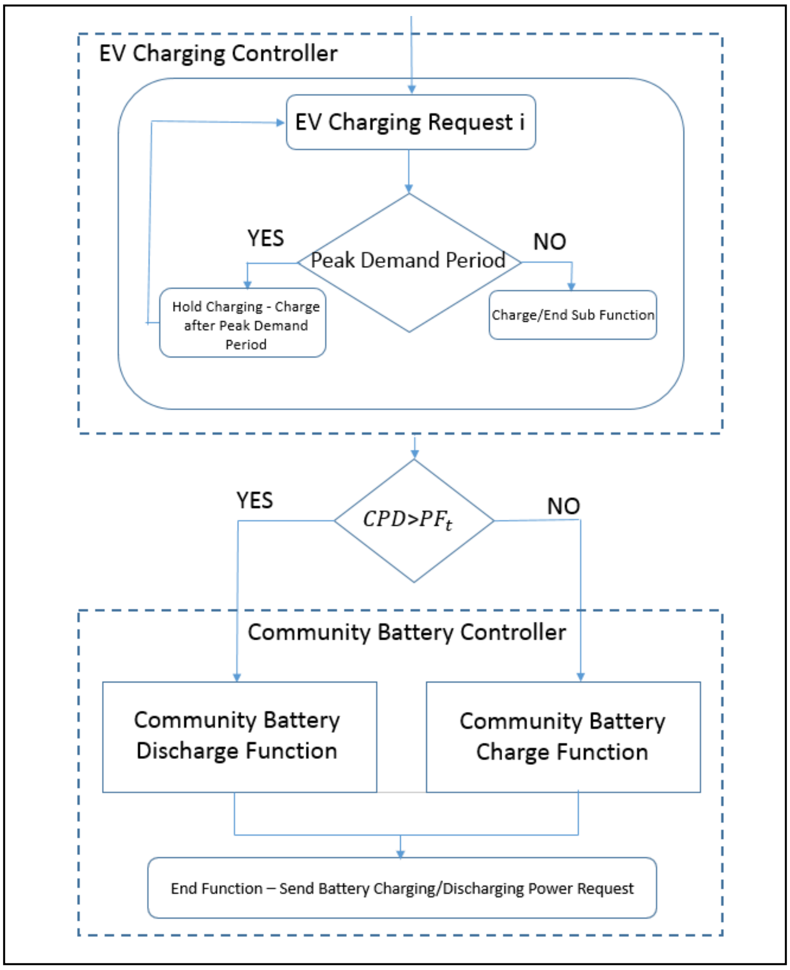
Given the expressed assumptions, the community real time controller can be simplified as follows. The developed real time controller structure and details are presented in the next section

4.5.2 Real Time Power Flow Controller

The developed real time controller structure is given in Fig. 4.12. As it is clearly visible in the structure flow chart, the controller is divided into two main control sub functions:

1) The EV charging control function

2) The community battery controller



Fiq. 4.12 Power Flow-Community Real Time Controller Structure

4.5.2.1The EV Charging Controller

The EV control function was chosen as the only demand management part of the developed real time controller due to the fact that as EV penetration increases this will become by far the dominant shiftable load. Each EV charged by a domestic electric socket is a demand load equal to 3kW. In a small community with a high penetration of EV, the aggregated demand from the charging EVs can be at times disproportionally large compared to the overall community demand. If for instance in a 100 dwellings community 50 EVs exist and during the peak time demand period 25 of them required charging the demand only from the EV will be equal to 75 kW. If that demand is compared to the average demand during peak time that might constitute up to a third of that.

A comparison of the demand of a community with and without EVs charging within a simulated community, for a weekday, is given in Fig. 4.13. Our simulated community consists of 100 dwellings with 50EVs.

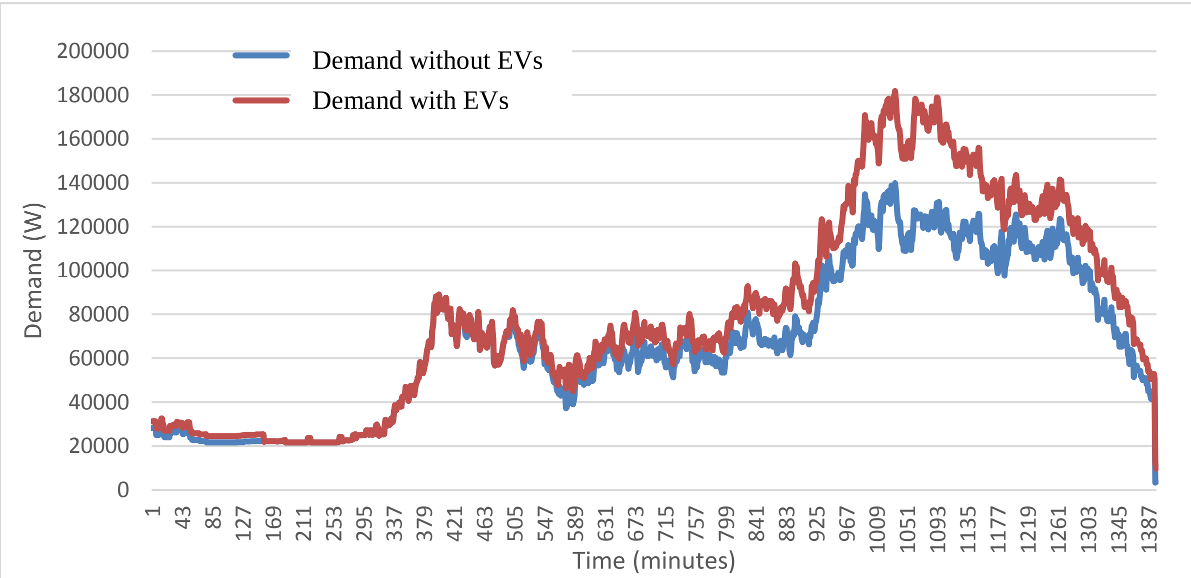


Fig. 4.13 Comparison of demand with and without EVs of a 100 dwelling community with 50EVs

In Figure 4.13 of our simulated community the difference during peak demand period (16:00 – 23:00 hrs) can reach at times 65 kW. As it becomes obvious the charging demand of EVs during peak demand period should be controlled and is therefore included as an option to the real time controller.

The control is limited only during the peak demand period since it is the period with the greatest probability of an EV to return home and start charging. The controller does not allow the charging of EVs and delays the start until the end of the peak time period. After and before the peak time, the EVs can charge without any interference from the controller. If an EV starts charging before entering the peak time period, the charging procedure will not get disturbed and will continue until fully charged.

4.5.2.2 The Community Battery Controller

The second function is the battery controller function of the equivalent central community BESS. This function is responsible to control the charging and discharging power request from the battery ESS according to (4.6)

$$P_{BD} = CPPT_t - CPD + RG_{PV} \qquad (4.6)$$

The equation describes the power difference between the community power profiling target ($CPPT_t$) demanded by the higher hierarchical level, the local renewable generation from PV systems located in the community (RG_{PV}) and the community consumption power demand (CPD) to cover all the load demand requests that exist at every time step. This difference is the reference for the charging/discharging power required by the BESS. This allows the community reference power flow to match the community power profiling target.

4.6 Real Data Resources and Usage

4.6.1 Introduction

Finally, as part of the proposed community cells level, roof mounted photovoltaic systems as the main mean of localised renewable generation in residential communities constitute an important part of the lower level cell. Although a large number of PV models are available in the literature [68, 69, 70], the utilisation of an existing model is considered unnecessary. The power generated by real residential PV systems existing across the UK for time periods longer than a year and with high resolution, are widely available and are considered the best option.

Furthermore, as seen by the proposed hierarchical framework structure in Fig 3.1, the highest hierarchical level consists of the DNO. As the highest level, one of the primary roles of a DNO according to [39] is to provide effective and efficient provision and balancing of network capacity. As a conscience part of its role is to coordinate the frequency regulation requests towards the mid-level ACPP-EMS. To simulate these requests towards the ACPP-EMS controller a mechanism had to be created that resembles real life, in terms of regulation request frequency and time of the day throughout the year, in the most accurate possible way. In order to achieve that, real life, high resolution frequency data of the UK electricity grid were used.

Details of real data used and how they were manipulated are given in the next section.

4.6.2 Real Data Resources

4.6.2.1 PV System

Starting from the Photovoltaic system, a real 3.8 kWp PV system located in the Trowel area in greater Nottingham was used as the primary source of data. The system uses 20 Schüco 190 MS 05 panels of 190 Wp each and an SMA Sunny Boy SB 4000 TL inverter with a rated power of 4 KW and maximum efficiency of 97%.

The PV generation data are available through PVOutput.org [71], a free organisation for sharing, comparing and monitoring live solar photovoltaic data. The data is published at 5 minute intervals and were gathered for a whole year (365 Days). The gathered data was used as the base for the required PV generation model during the simulation process and were scaled up according to the PV penetration assumption made, during the different simulation scenarios.

4.6.2.2 Frequency Regulation Requests

The second source of data used and analysed, were second by second electrical frequency data for the whole 2015, provided by National Grid [72] for support analysis of frequency response purposes.

The proposed ACPP-EMS is considered a part of the post-fault secondary response service which is responsible for restoring the frequency to operational limits after breaching the 49.8 -50.2 Hz limit. Therefore, the frequency data is processed such that when these limits are breached a request is considered to be made by the DNO.

In order to gain a better understanding of the frequency data of how often errors occur in different seasons of the year, based on the 2015 electrical frequency data, histograms were created. An example for December is given below in Fig 4.14. The X axis is the 48 half hour segments of each day. The frequency analysis is made in half hour segments due to the 30 minute operational frequency of the novel ACPP-EMS controller that will be presented in Chapter 5.

December - Number of Frequency Limit Breaching

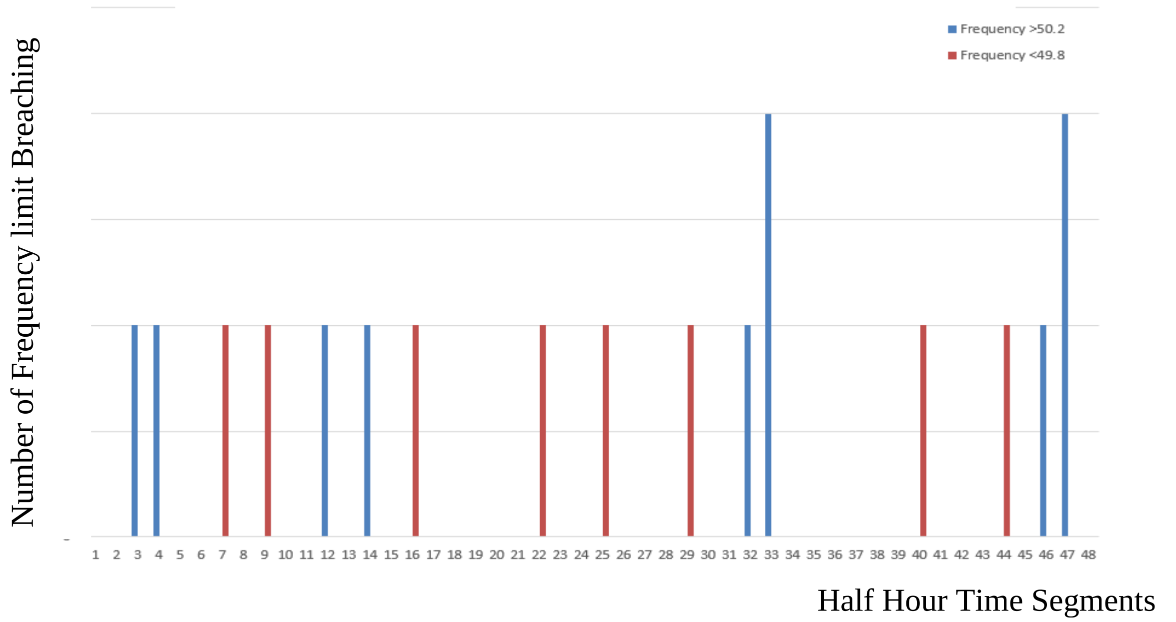


Fig. 4.14 Frequency limit breaching occurred during December in the same half hour time segments.

As it can be seen in Fig 4.14 the number of times the frequency breaches the limits are limited into only 18 times for a whole month or a percentage of around 0.01% of the time. The limit breaching also occurs in random time segments making it very difficult to use prediction techniques in order to prepare for future errors. Errors when the frequency is higher than 50.2 Hz are given in blue and errors where the frequency is lower than 49.8 are given in red. A more detailed analysis of frequency errors will be given in chapter 6.

4.7 Energy Storage System Sizing

The “community cell” used during the results chapter (Chapter 6) includes an aggregated ESS with a capacity equal to 350 kWh. To determine that capacity of the system, this section presents a novel sizing method based on chosen confidence levels. The idea of using confidence levels as the base for the proposed procedure originated from a sizing procedure proposed by Chen et al [73] were confidence levels of dispatchability were used to size ESS for wind farms in order to achieve more predictable energy outputs. Following a similar line of thought, due to the fact that a future community load profile that is dominated by a large number of EVs and roof mounted PV systems can be highly unpredictable, a sizing procedure based on confidence levels to achieve power targets would be ideal.

Energy storage sizing includes the determination of the capacity of an ESS and its rated power. The rated power of the system should be enough to cover the power differences between targeted power and actual power demand and the capacity should be large enough to provide the required energy for requested charging/discharging time periods. In the following sections the proposed ESS sizing method is presented.

The size of an ESS changes according to the required confidence a target set. If a predetermined power target must be achieved 100% of the time, a much larger ESS will be needed compared to a system that is only expected to reach the target for 80% of the time.

The higher hierarchical level target used for the calculation of the size of the ESS for the presented method is constant and equal to the net yearly average power demand. At the lower community cell level, the real time controller is responsible to follow the incoming target through the control of the local ESS charging and discharging.

4.7.1 Methodology

The Sizing method is based on the confidence levels. The confidence level of target achievability is the likelihood of the community achieving the predetermined power target using the energy storage system available. The probability of the community cell to meet the target through the available ESS can be expressed as:

$$S_i = \begin{cases} 1: P_i \leq P_{rated} \; \& \; SOC_l < SOC_i < SOC_h \\ 0: P_i > P_{rated} \text{ or } SOC_i \leq SOC_l \text{ or } SOC_i \geq SOC_h \end{cases}$$

Where S_i represents the state of success of achieving the power target at the *i*th time period, P_i is the power request from the available ESS at the *i*th time period, SOC_i is the State Of Charge of the ESS at the at the *i*th time period, SOC_l is the lower limit of state of charge and SOC_h the higher limit of state of charge. Then the confidence level of achieving the power target is given by (4.7)

$$P_{cta} = \sum_{i=1}^{N} \frac{S_i}{N} \qquad (4.7)$$

where N is the total number of samples.

The definition of state of success includes the success of power being lower than the rated power and energy success being within the capacity limits.

Starting from the ESS power rating the first part of the method is the determination of the minimum power rating of the converter where the requested confidence level can be achieved. In order to determine the minimum ESS power rating to achieve a predefined confidence level the following iteration procedure should be followed:

ESS Minimum Power Rating:

1) Define the confidence level (P_d).
2) Initialisation: ESS power rating (P_{ESS}) = maximum power requested, ESS capacity = "infinite".
3) Run the simulation environment and calculate confidence level (P_{cta}) according to (4.7)
4) If confidence level ($P_{cta} > P_d$) or ($P_{cta} < P_d$), increase or decrease the ESS power rating (P_{ESS}) and return to step 3.
5) When $P_{cta} = P_d$ the minimum power rating to achieve the required confidence level (P_d) is found.

During the first step of the method the ESS capacity is kept "infinite" in order to pinpoint the minimum power rating to achieve the required confidence level without being affected by capacity related zero state of success events. The term "infinite" capacity is defined as a non-realistic very large capacity rating i.e equal to twice the yearly energy demand of the community the ESS is sized.

Having identified the minimum power rating for the required confidence level, the next part of the sizing methodology is to pinpoint the minimum capacity to achieve the same level of confidence under different ESS power ratings following a second iteration procedure. The procedure starts from the minimum power rating located at the previous section. The procedure steps are:

1) Initialise the ESS power rating (P_{ESS}). Initialise the P_{ESS} to be 5 KW higher than the minimum power rating achieved at the previous part of the sizing procedure, ESS capacity = "infinite".

2) Calculate confidence level (P_{cta}) according to (4.7).

3) If confidence level ($P_{cta} > P_d$) or ($P_{cta} < P_d$) increase or decrease ESS capacity and return to step 2.

4) When $P_{cta} = P_d$ the minimum power rating to achieve the predefine confidence level (P_d) is found. The minimum capacity under the ESS chosen power (P_{ESS}) is found.

5) Increase the ESS power rating (P_{ESS}) in 5 kW steps to the next power rating and return to 2).

Following the described sizing method, a group of capacity values for different power ratings at the same level of confidence is calculated. Curves can be plotted with the power ratings at the primary horizontal axis and the capacity required to achieve the defined confidence level at the vertical axis. The results for the 100 dwelling community, with 50 EVs and 120 kWp aggregated PV system as descripted in the section 6.3 for different confident levels are presented in Table 4.5 for a simulation period of a year.

Community: Residential 100 House PV penetration =40% /120KWp, EVs = 50%/ 50 Vehicles						
	90%Confidence		80%Confidence		70%Confidence	
	Power Rating (KW)	ESS Capacity (KWh)	Power Rating (KW)	ESS Capacity (KWh)	Power Rating (KW)	ESS Capacity Rating(KWh)
minimum Power Rating-infinite Capacity	70	-	57	-	47	-
	75	8000	60	3700	50	2000
	80	2500	65	500	55	400
	85	1000	70	400	57	350
	90	700	75	350	60	300
	95	600	80	350	65	275
	100	600	85	340	70	270
	105	590	90	335	75	270

Table 4.5 Results of capacity values under different power ratings for different confidence levels

The capacity values presented in Table 4.5 are the minimum capacity values for different power ratings to achieve desirable levels of confidence. The size of the ESS for a defined level of confidence should be chosen at or above the curve created by the power rating/capacity group as shown in Figure 4.15 for a 90% confidence level.

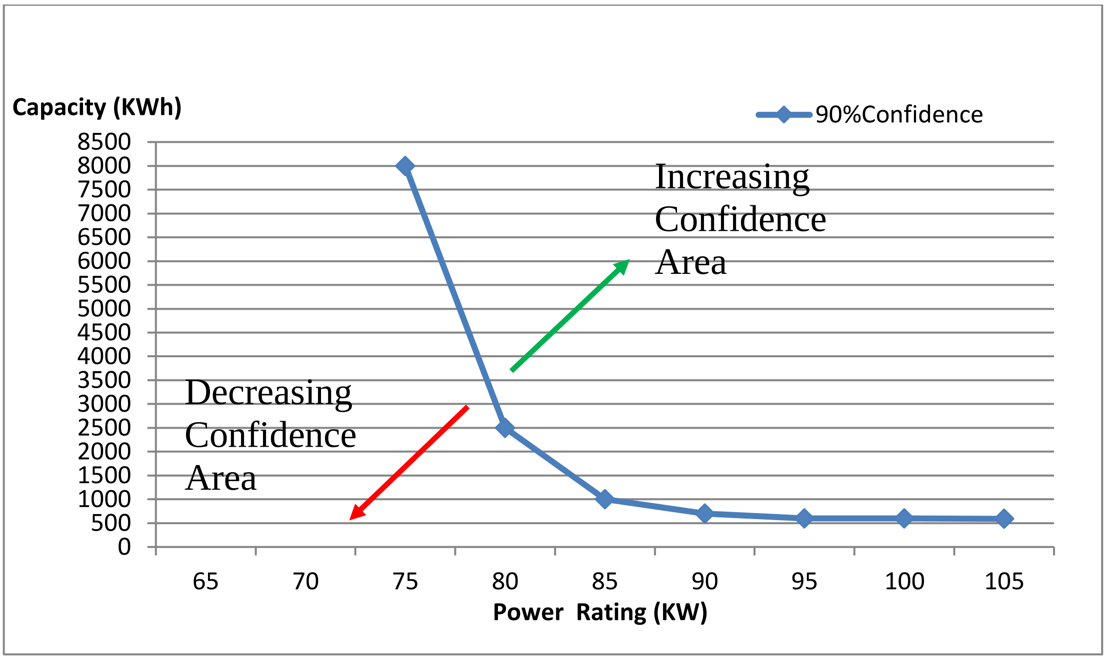


Fig 4.15 Curve of minimum capacities at a 90% confidence level

Based on the results, the ESS power rating /capacity groups can provide the same level of confidence for a number of combinations. A fast, easy and effective manner of choosing the best combination is the cost of the proposed ESS.

Using the available information about the TESLA powerwall Battery ESS [9], a 14 kWh powerwall battery and supporting equipment including VAT cost £5900. Resulting to a capital cost of £421.43 per kWh of installed capacity. Furthermore, according to SMA products manual an SMA Sunny Boy Storage 2.5 KW battery inverter costs including VAT £1000 [74]. Resulting to a capital cost of £400 per kW or a kilowatthour/kilowatt cost ratio r of 1.05. The choice of using the SMA inverter was based on the fact that Tesla suggests using it with the Powerwall BESS.

Using the above information, the total system cost is:

$$C_{total} = (S_C * 421.43) + \frac{S_{Pr}*421.43}{r} \quad (4.8)$$

Where C_{total} is the total cost of the ESS, S_c is the size of capacity in KWh of the proposed ESS, S_{Pr} is power rating size in kW of the proposed ESS and r is the kWh/kW cost ratio. The outcome of the cost analysis is presented in Table 4.6. The optimum choice, in terms of cost, for every confidence level is noted with a yellow colour.

90%Confidence			80%Confidence			70%Confidence		
Power Rating (KW)	ESS Capacity (KWh)	Total Cost(£)	Power Rating (KW)	ESS Capacity (KWh)	Total Cost(£)	Power Rating (KW)	ESS Capacity (KWh)	Total Cost(£)
70	-	-	57	-	-	47	-	-
75	8000	3231607	60	3700	1505286	50	2000	821072
80	2500	1033714	65	500	227393	55	400	183179
85	1000	435822	70	400	189500	57	350	164022
90	700	317929	75	350	171607	60	300	145286
95	600	280036	80	350	173714	65	275	137393
100	600	282143	85	340	171822	70	270	137500
105	590	280250	90	335	171929	75	270	139607

Table 4.6 Results based on total cost for different confidence levels for the proposed rating /capacity groups.

The proposed novel sizing method presents a fast, transparent and easily executable procedure for sizing ESS according to the predefined needs (confidence) of the owner of the system with respect to the community size.

4.8 Conclusion

In the presented chapter all the required models in order to simulate the lower level "community cell" of the proposed hierarchical structure were introduced. A number of the required models was adopted from the available literature or developed to meet the needs of the simulation procedure. Furthermore, when possible data acquired from real resources were introduced.

As part of this chapter a residential electricity demand model and a battery energy storage system (BESS) was adopted from models already available in the existing literature. In addition, a novel electric vehicle model (EV) was developed and a lower level real time power flow controller was introduced. Furthermore, real data from photovoltaic systems and the electrical system frequency data were analysed and used as part of the simulation procedure. Finally, a novel ESS sizing methodology was also developed to size the "community cell" aggregated ESS.

In the following chapter the novel higher-level controller the Adaptive Community Power Profiler- Energy management System is presented

Chapter 5: Adaptive Community Power Profiler (ACPP) – Energy Management System (EMS)

5.1 Introduction

Chapter 5 will introduce the Adaptive Community Power Profiler (ACPP) – Energy Management System (EMS). The ACPP-EMS is a novel higher-level controller which forms the mid-level part of the proposed hierarchical framework presented in chapter 3. The control algorithm developed in this project will provide community power profiling targets ($CPPT_i$) to each of the community cells in the controlled area. The controller operation logic, implementation and communication requirements are presented in detail in the following sections.

The basic building blocks of the proposed higher-level controller are presented in Figure 5.1. In order for the ACPP-EMS controller to generate the Community Power Profiling Targets ($CPPT_i$) a number of auxiliary blocks are required to work in cooperation with the main ACPP-EMS algorithm to provide and analyse information before it is used by the main controlling logic.

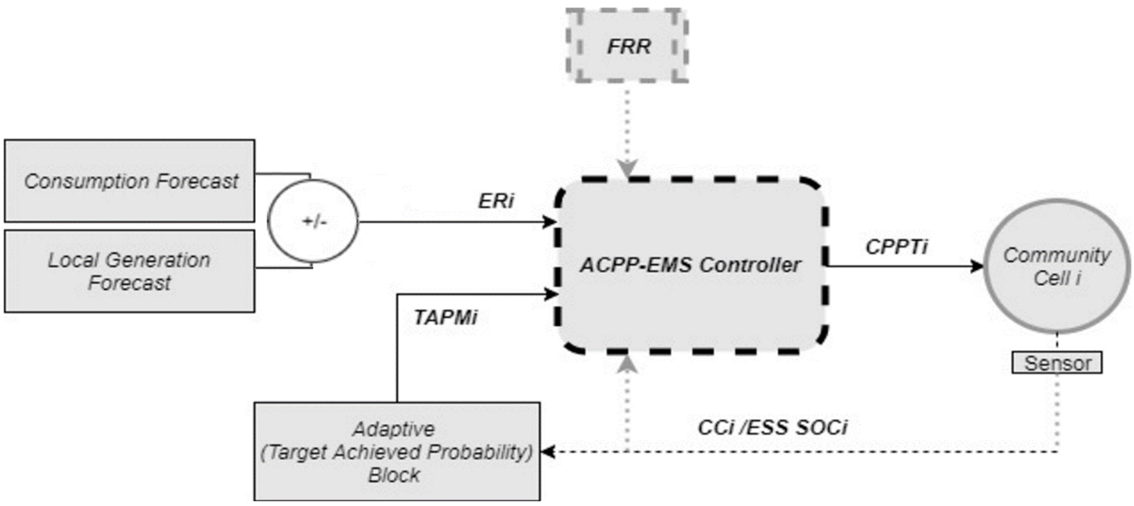


Fig. 5.1Adaptive Community Power Profiler (ACPP) – Energy Management System (EMS) Basic Building Blocks

The main auxiliary blocks of the ACPP-EMS controller as presented in Figure 5.1 are:

- The community "Consumption Forecast" block and the "Local Energy Generation Forecast" block which combine to give one Energy Request (ER_i) input. The two blocks are responsible for forecasting the near future demand and renewable generation of the community cell and provide the results to be used by the main ACPP-EMS controller.
- The "Adaptive Block" or "Target Achieved Probability Matrix" ($TAPM_i$) created to provide information of the probability of achieving a profiling target using past tested targets by the community cell at particular times and specific SOC of the aggregated community ESS.
- The "Frequency Regulation Request" (FRR) input from the higher DNO level. As presented in chapter 3, the ACPP-EMS controller was developed with the ability to become part of a new frequency regulation service. When the higher, DNO level, requests its frequency regulation services, the controller is responsible for providing the requested service based on what can be achieved by the controlled area at that particular time. The FRR was created to simulate the regulation requests made by the DNO during the tested time period based on real data provided by National Grid.

Having introduced the main auxiliary blocks, the communication requirements between the blocks and the ACPP-EMS controller and also between the controller and the community cells in the control area will be also introduced in the following sections. As illustrated in Figure 5.1 the community cell provides feedback to the ACPP-EMS controller but also to the Auxiliary Target Achieved Probability block ($TAPM_i$). The feedback consists of the

Community cell Consumption (CC_i) at the point of common coupling and the communities aggregated ESS SOC provided by the lower level real time controller.

It is really important to highlight that the operating frequency of the ACPP-EMS controller is 30 minutes. The controller generates its targets in Half Hour Blocks (HHB) and the generated target should be followed by the low-level real time controller for the next 30 minutes until a new $CPPT$ is generated. The 30 minute operating frequency was chosen for a number of functional reasons.

- Firstly, when taking part in the frequency regulation market and particularly in frequency regulation by demand management it is a requirement according to National Grid published reports [74] to sustain the agreed power demand for a duration of 30 minutes. Based on that requirement, having a 30 minute operating frequency is a reasonable next step.
- Secondly by separating the day into 48 HHB the information required to handle is reduced to a level that is not prohibiting, in terms of volume of communication, data processing and storing. Instead of having to handle, save and process information for every minute of the day, information can be aggregated and processed in half hour time blocks minimising the communication and processing burden.
- Finally, since the ACPP-EMS controller is an intermediate hierarchical stage between the higher DNO and the lower real time community cell controller, it is required to operate at a frequency that does not create instabilities for the lower level because of targets changing rapidly and at the same time can be in synchronisation with the higher DNO level.

Due to the above all the auxiliary blocks and communication signals also follow the half hour operation frequency.

5.2 Auxiliary Blocks and Communication Requirements

Beginning from the auxiliary blocks in the following sections each block will be presented and analysed separately. Starting from the Consumption and Local Generation Forecast blocks, followed by the Target Achieved Probability block and finally the Frequency Request block representing the DNO requests for frequency regulation ancillary services.

At section 5.2.2 the communication requirements will be explained. The controller is constructed with the main ACPP-EMS controller and all the auxiliary blocks running together as one entity, consequently minimising the communication requirements. As a result, the communication requirement exists only between the community low level real time controller and the proposed higher level ACPP-EMS controller on one side and the DNO and the controller from the other highest hierarchical side.

5.2.1 Auxiliary Blocks

5.2.1.1 Forecast

Short term forecast in terms of community renewable generation and community load demand are a really important part of the information input required by the main ACPP-EMS controller. Short term forecast is the prediction of the future trends in time intervals, extending from a few hours to a number of weeks. In this project, short term forecasting refers to the next day (24 h) forecasting. As can be seen in Figure 5.1, two auxiliary blocks are responsible for forecasting the near future demand and renewable generation of the community cell and provide the results to be used by the main ACPP-EMS controller.

In the available literature a number of forecasting techniques have been used for both load and renewable generation forecasting. The most commonly encountered include statistical linear regression techniques [76] usually represented by the auto-regressive integrated moving average (ARIMA) prediction method and the non-linear expert systems methods represented by fuzzy logic [77] and neural networks [78] or a combination of the these.

Examining the above prediction approaches in terms of residential electrical demand forecasting in small residential communities Marinescu et al. [79] concluded that none of the evaluated method has advantages and disadvantages and cannot be selected at the expense of others. Based on a scenario of 90 dwellings for a 24 hours ahead prediction the regressive statistical approaches provided the best overall prediction with a normalised mean square error equal to 3.63%, with the fuzzy logic approach having good morning peak prediction and the neural networks the best evening prediction.

Furthermore, a comparison of short–term forecasting of PV generation for the day ahead including linear regression statistical approaches, neural networks and persistence method is presented by Kardakos et al. [38]. The persistence method for the comparison is defined as the generation in each hour of the forecast day equals the real PV generation of the respective hour of the previous day. Based on the presented results the statistical methods had the best overall forecasting capability, with a year average error of 11.12%, the neural network approaches having a year error between 11.26-11.42% and finally the persistence approach with an error of 13.71%.

Although the results presented do not give a clear answer to which of the methods can be considered the best to be used, they clearly indicated that the difference between them is quite small and even the simplest, persistence method, can provide comparable and relatively good forecast capabilities. Since forecast techniques are out of the scope of this project and in order to minimise the computational burden and the time required to run simulations to acceptable time scales, it was preferred to keep the forecast techniques as simple as possible. At the same time by accepting the highest possible errors in our demand and generation forecasts, the proposed Adaptive (Target Achieved Probability) Block and ACPP-EMS controller will be tested and optimised under adverse condition making any future improvements in forecast techniques highly beneficial for the controller performance.

The community demand forecast block is therefore based on the persistence model. According to the persistence model, for every weekday, the demand in each hour of the forecast day equals the demand generation of the respective hour of the previous weekday. For weekends the demand in each hour of the forecast day equals the demand of the respective hour of the previous same weekend day. The model is presented in (5.1).

$$P(h) = \begin{cases} P[h-24] & \text{Weekday} \\ P[h-(6*24)] & \text{Weekend} \end{cases} \quad (5.1)$$

where *P(h)* is the demand prediction for hour h, *P[h-24]* the previous day real demand at the same hour and *P[h-(24*6)]]* the previous weekend day real demand at the same hour.

Following the same reasoning and according to the results presented by Kardakos et al. [38], the persistence method results calculated, change according to the season with the worse being in winter with errors up to 20%. In order to test the controller and optimise under the most unfavourable condition, the local PV generation forecast was considered to be the actual generation with an added random error varying between 0-20% for every hour. The expression is given in (5.2)

$$PV_g(h) = PV_{ga}(h) \pm \left[PV_{ga}(h) * [r]\right]$$
$$r = [0 - 0.1] \tag{5.2}$$

where $PV_g(h)$ is the PV generation prediction for hour h, $PV_{ga}(h)$ is the actual PV generation at the same hour and r is a random error introduced between 0 and 10%.

5.2.1.2 Adaptive Block or Target Achieved Probability Matrices ($TAPM_i$)

The novel adaptive block or Target Achieved Probability Matrices ($TAPM$) is a mapping matrix that provides a record tool of the proposed Community Power Profiling Targets ($CPPT_i$) for the ACPP-EMS controller. Through the $TAPM$ matrices, a constantly updated record is obtained, where the parameters, the proposed profiling targets and the targets success or fail to be achieved by the lower level community cell level are registered.

The driving force for creating this auxiliary block was the creation of a record, for each community cell under control of how well it achieves the imposed profiling targets. By having this mapping tool available for the higher-level controller, profiling targets can adapt to achieve important goals with high success probability when it is necessary.

In the proposed hierarchical structure, this record is accessed when a frequency regulation request is made by the highest DNO level as described in chapter 3. After the request by the DNO is made, the ACPP-EMS controller is responsible for publishing what it can achieve in terms active power import adjustment. At this stage, if its offer gets accepted, no errors in achieving the proposed power import adjustment are allowed and the proposed profiling target ($CPPT$) should be achieved by the community for the next 30 minutes without any deviation. In order to achieve the level of confidence required, a record of profiling targets imposed, under what parameters and the probability of success for each community cell is critical.

To create the $TAPM$ mapping record for each community cell in the control area, a number of parameters should be taken into account. The aggregated SOC of the available ES inside the community cell, the target imposed by the higher level ACPP-EMS controller for the community cell and if the imposed target to the community cell was successfully achieved are recorded.

The profiling targets are divided in to bins of 10 kW each, starting from 0 up to 160 kW. The same strategy is followed with the SOC of the aggregated ES system, the SOC is divided into 10% SOC bins. As it can be seen in figure 5.2, by following the above strategy for the community cell a two-dimensional matrix is created, for each half hour block, with the rows representing the profiling target bins and the column the aggregated community ESS SOC. Each element of the matrix includes the probability of achieving an imposed profiling target by the community cell under control at a specific SOC. The way this record is populated is discussed below.

1 Month	**SOC**						
Target (kW)	25-35	35-45	45-55	55-65	65-75	75-85	85-95
0-10	0	0	0	0	0	0	0
10-20	0	0	0	0	0	0	0
20-30	0	0	0	0	0	0	0
30-40	0	0	0	0	0	0	0
40-50	0	0	0	0	0	0	1
50-60	0	0	0	0	0	0	1
60-70	0	0	0	0	0	1	0.4
70-80	0	0	0	0	0	0	0
80-90	0	0	0	0	0	0	0
90-100	0	0	0	0	0	0	0

3 Months	**SOC**						
Target (kW)	25-35	35-45	45-55	55-65	65-75	75-85	85-95
0-10	0	0	0	0	0	0	0
10-20	0	0	0	0	0	0	0
20-30	0	1	0	1	0	1	0
30-40	0	0	0	0	0	1	1
40-50	0	0	0	0	1	1	0.78
50-60	0	0	0	0	0	1	0.75
60-70	0	0	0	0	0	1	0.44
70-80	0	0	0	0	0	0	0.18
80-90	0	0	0	0	0	0	0
90-100	0	0	0	0	0	0	0

100-110	0	0	0	0	0	0	0		100-110	0	0	0	0	0	0	0
110-120	0	0	0	0	0	0	0		110-120	0	0	0	0	0	0	0
120-130	0	0	0	0	0	0	0		120-130	0	0	0	0	0	0	0
130-140	0	0	0	0	0	0	0		130-140	0	0	0	0	0	0	0
140-150	0	0	0	0	0	0	0		140-150	0	0	0	0	0	0	0

Table. 5.1 12 HHB (05:30-06:00) Charging Target Achieved Probability Matrix ($cTAPM$). Left – matrix after 1 month of operation. Right –matrix after 3 months of operation.

Table 5.1 presents how a TAPM evolves and updates over time. Each TAPM for that specific HHB is updated every time a profiling target is imposed on the community cell. When the new profiling target is given to the community cell, the adaptive block holds the target and the aggregated SOC of the community ESS. At the same time the community power input is compared with the profiling target. When the half hour under discussion has finished, the adaptive block in the particular two-dimensional TAMP locates the element representing the correct profiling target/SOC bin and updates it according to (5.3).

$$N_s = \begin{cases} 1 & \text{,Success} \\ 0 & \text{,Failure} \end{cases}$$

$$P_e = \frac{\sum_i^n N_s}{\sum_i^n N_t} \tag{5.3}$$

where N_s is the success or failure of the community cell in following the given profiling target at the specific SOC, N_t is the total number of times that target was tested at the specific SOC and P_e is the achieved probability of the specific element target. As it can be observed in figure 5.2 the target achieved probability is formed of numbers up to 1, 1 is a 100% success rate. Number zero (0) is used for non-tested matrix elements.

Comparing the two matrices in table 5.1 it can be immediately observed how the percentages of the target achieved probability change for the tested elements as time passes and more information is available. As new information becomes available and the sample-set of the tested targets becomes bigger, the probabilities a community cell achieving a given target becomes more accurate.

New targets are also tested and the matrix is enriched with every passing day. Due to the controlling logic of the ACPP-EMS controller the adaptive block becomes even more valuable, as the profiling target generation relies on forecasted data as explained in section 5.2.1.1. The forecasted values, no matter how good the forecasting techniques used, always contain an error. Through the adaptive block, that error is reflected in the target achieved probability of each element for a specific proposed profiling target and SOC. Hence the forecast errors are also taken into consideration at the main ACPP-EMS controller block via the adaptive block for each half hour cycle.

As a whole, the Adaptive Block can be perceived as a three-dimensional matrix or a number of two-dimensional TAPM over time as can be seen in Figure 5.2. As has been stated the operational sample time of the ACPP-EMS controller is 30 minutes. The controller generates its targets for Half Hour Blocks (HHB) and the generated target should be followed by the low level real time controller for the next 30 minutes until a new $CPPT$ is generated. Following the above reasoning for the weekdays there are 48, two-dimensional 15X7 matrices and 48 similar matrices for every weekend. Furthermore, these are different for charging and discharging profiling targets, therefore totalling to 192, two-dimensional TAPMs for each community cell in the control area.

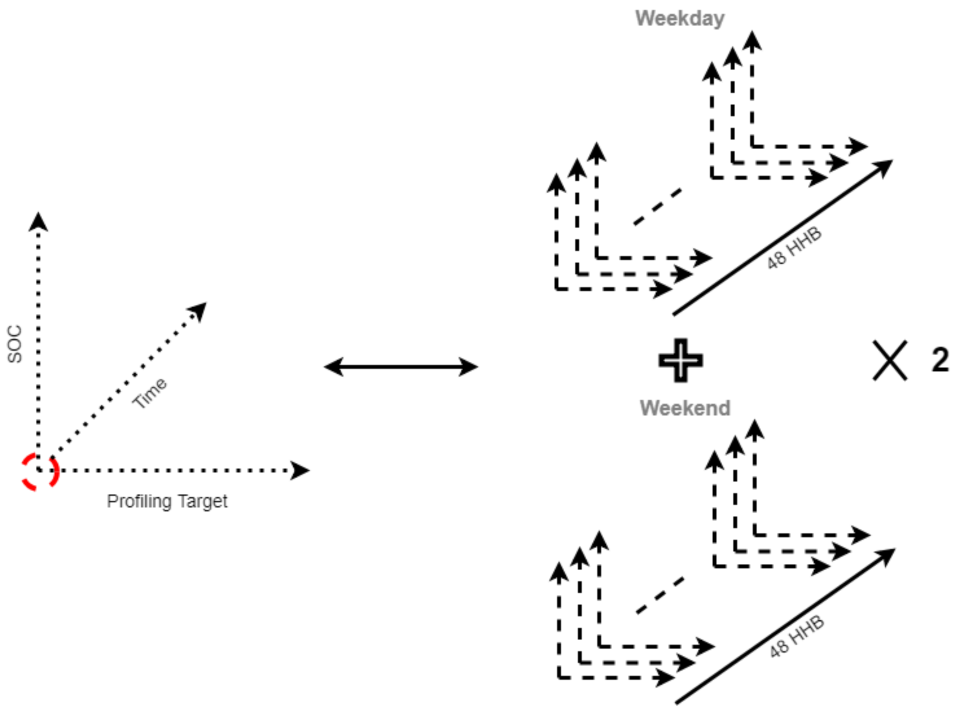


Fig. 5.2 Number of TAPM in each adaptive block

In conclusion the adaptive block is a constantly updated, computationally efficient and relatively simple to implement, community's record that can provide significant information about the behaviour of a community cell. This is critical when an error cannot be tolerated or the occurrence of an error automatically implies a failure to fulfil agreed obligations and even the imposition of a large financial penalty.

5.2.1.3 Frequency Regulation Request (FRR)

The Frequency Regulation Request (FRR) (shown in figure 5.1) was created to simulate the frequency regulation requests by the highest/DNO level in the proposed hierarchical structure. In order to achieve as realistic a result as possible, real raw second by second electrical frequency data was obtained for the year 2015, provided from National Grid [72] to support the analysis of frequency response capability. Based on the raw data and considering the ACPP-EMS controller as part of the post-fault secondary response service (responsible for restoring the frequency to operational limits after breaching the 49.8 -50.2 Hz limit) the frequency data were cleared, analysed and frequency regulation requests were extracted. To extract the frequency regulation requests the yearly data was analysed and the times where the operational limits are breached were identified and recorded.

Since the ACPP-EMS controller operating time is 30 minutes, to avoid compatibility issues, the raw 2015 frequency data was also analysed in 30 minutes (Half Hour) time blocks. The first step for the analysis was to investigate whether repeating patterns for the frequency requests could be detected or whether they are random events and they need to be addressed in that manner. To investigate for patterns, the correlations among half hour frequency requests from day to day and between the first day and previous days was computed and plotted. The correlation coefficient was calculated according to (5.4).

$$r = \frac{\sum_i [(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum_i (X_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2} \qquad (5.4)$$

where x_i, y_i are the compared variables, $\bar{x}, \bar{y}$ their average value for the comparison period and r the correlation coefficient. The correlation coefficient (r) can take values between 1 and -1, r = 1 means perfect positive correlation and r = -1 perfect negative correlation. A sample of the computed results are plotted in Figure 5.3, 5.4.

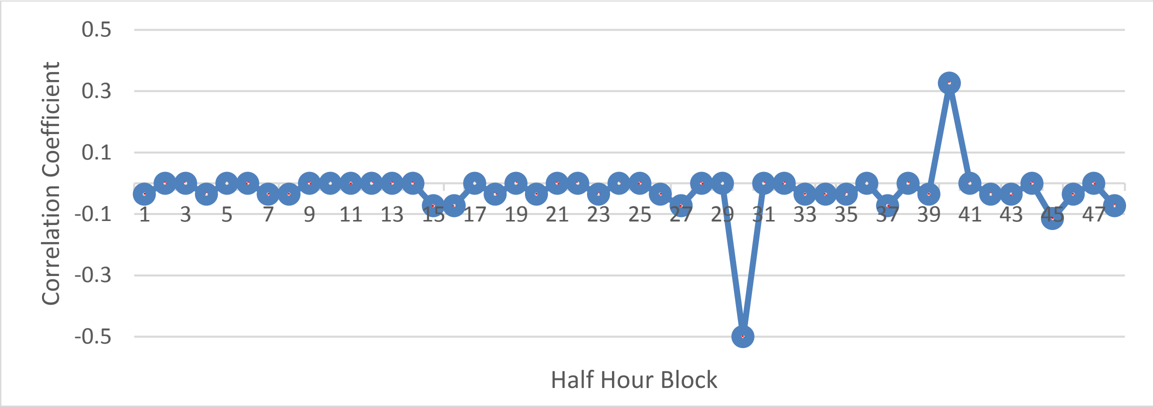


Fig. 5.3 Correlation coefficient of November Frequency regulation requests from day to day.

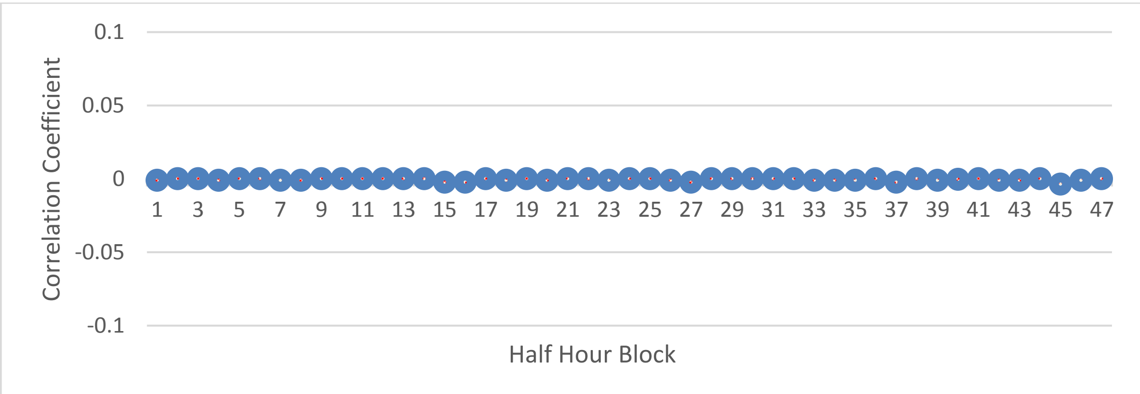


Fig. 5.4 Correlation coefficient of November Frequency regulation requests between 30st day and previous days of the month.

The plotted correlation coefficient presented in Figures 5.3 and 5.4 are for a 30 day period in November. As can be clearly observed the correlation coefficient from one day to the next in Figure 5.3 is insignificant and no patterns can be detected from the correlation results. In Figure 5.4 the correlation between one day and the previous days of the same month, are even worse than the day to day correlation and are almost equal to zero. The correlation coefficient analysis leads to the conclusion that past frequency regulation requests cannot be used as an indication for future requests and they need to be addressed as random events.

In this context, the FRR block is used to generate the frequency regulation requests for the ACPP-EMS controller as they are extracted from the raw [72] 2015 electrical frequency data using one restriction, which is that one frequency regulation request can be made every six hours. The assumption of a six hour gap between requests was adopted for practical reasons as will be described in the following paragraph.

After a power profiling target is agreed with the DNO for frequency regulation purposes, after fulfilling its goal, the ESS should charge or discharge to its previous state. When a frequency regulation request is made, for example to minimise demand, after the usage of the available ESS capacity, the ESS will need to recharge. Having a window of six hours for recharging, the power demand will be relatively low when compared to the community's peak power demand. If for instance the ESS capacity required to be used for frequency regulation purposes is 150 kWh, the demand for recharging the ESS in the following six hours will be equal to 25kW. Thus, the community's behaviour during this charging or discharging period will not drastically change by creating unexpected peaks or troughs to the overall community cell power demand.

5.2.2 Communication Requirements

As presented in Figure 5.1, the controller block is constructed with the main ACPP-EMS controller and the auxiliary blocks running together as one entity, consequently minimising the communication requirements. As a result, the communication requirement exists only between the community cell at the low level real time controller and the proposed higher level controller on one side, and the DNO and the controller from the other (highest) hierarchical side. An analytical representation of the ACPP-EMS controller with the other hierarchical levels in the proposed structure is presented in Figure 5.5.

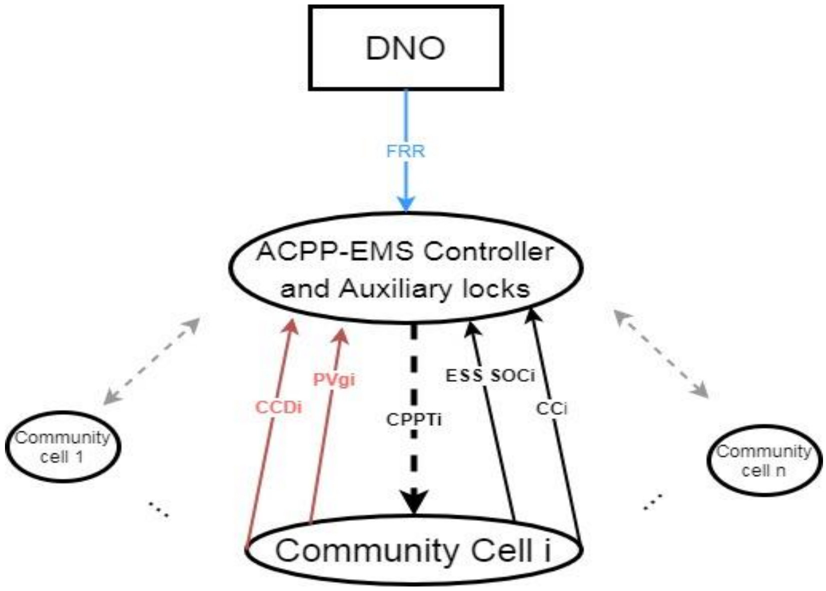


Fig. 5.5 ACPP-EMS controller communication requirements

Starting from the communication requirements between the lower level community cell and the ACPP-EMS controller, the red colour in Fig. 5.5 shows the communication requirements for forecast purposes and the black colour shows the information to be used by the controlling and adaptive logic of the controller.

The ACPP-EMS controller generates the targets for each community cell for the next 24 hours. Each auxiliary forecast block as presented in section 5.2 needs to generate (before midnight of each day) for the next 24 hours, a demand and PV generation prediction for each community cell. In order to achieve that, information about the most recent community cell demand request (CCDi) and PV generation (PVgi) from the community cell should be communicated to the higher level. That can be achieved with different methods, either by accumulating the data at the lower cell level and transmitting them to their destination as one big block of information or by transferring them when available in small information blocks.

In this project the latter was chosen as a more secure method since even in the event of communication loss the amount of data lost will be minimal and will be limited to only the previous half hour. Community cell demand (CCDi) and PV generation (PVgi) data are communicated to the higher level auxiliary forecast blocks in half hour segments using the same operational frequency scale of the ACPP-EMS controller.

Continuing with the communication requirements used by the controlling and adaptive logic of the controller (as presented in figure 5.5). Black arrows represent the aggregated community ESS State of Charge (ESS SOCi) and the community input power or community consumption (CCi) for the previous half hour block. The CCi is the real community consumption after a profiling target is imposed and the lower level real time controller attempted to implement the aforementioned target.

Depending how a controlled community is electrically structured, the communication requirement for the CCi, between the low level real time controller and the higher level ACPP-EMS controller can vary. If a controlled community is assumed to be fed by the same feeder of the substation, then the actual community half hour power import can be directly measured at the secondary substation feeder level and remove the need to communicate that information by the low-level controller. On the other hand, if we assume that a controlled community is electrically dispersed on a number of different electrical circuits, the information can only be provided by the community cell real time controller. Assuming the second as a more general case that includes the first one, the community consumption is communicated to the higher level for each half hour block by the community cell controller.

The need for a CCi exists due to presence of the adaptive block as described in 5.2.1.2. As part of the adaptive block, a comparison should be made in order to conclude if the profiling target (CPPTi) imposed by the ACPP-EMS controller was successfully/unsuccessfully achieved by the community cell and in turn according to (5.3) calculate the target achieved probability rate for the respective TAPM part of the adaptive block.

In contrast with the CCi feedback requirement, the aggregated community ESS SOC feedback requirement serves both the adaptive and the controlling logic of the controller at different times. Firstly, starting from the adaptive auxiliary block, as stated in section 5.2.1.2, the ESS SOCi creates the columns section of each two-dimensional TAPM matrix for a specific HHB where each element of the matrix includes the probability of achieving an imposed profiling target. This aggregated ESS SOCi information is communicated every half hour between the community cell real time controller and the auxiliary adaptive block at the higher ACPP-EMS controller level.

Secondly the aggregated ESS SOCi is also used by the controlling logic of the ACPP-EMS controller at the higher hierarchical level before calculating the profiling targets for the day ahead. The controlling algorithm can generate more accurate profiling targets if the information about the real aggregated SOC can be acquired and avoids the use of pre-calculated or assumed SOC as a starting point for the available community cell ESS capacity. This information is required as an input to the ACPP-EMS controller at midnight before the generation of the next 24 hours profiling targets. Nevertheless, as failsafe mechanism the controller can still operate without the information available based on an assumed ESS SOC at the end of the previous night.

Finally from the higher hierarchical level down, the profiling power targets (CPPTi) need to be communicated to the controlled community cells for every half hour of the next 24 hours. The profiling targets in the simulated structure of this project, are published every half hour by the ACPP-EMS controller for the future half hour time block and transmitted to the community cell i in the controlled area.

Beside the communication requirement between the ACPP-EMS controller and the community cell level, another communication channel needs to be established between the controller and the highest DNO level of the hierarchical scheme. This communication is required to allow the ACPP-EMS controller to become a part of the frequency regulation market. In the simulated environment of this project the DNO is substituted by the Frequency Regulation Request (FRR) block presented in the previous 5.2.1.3 section.

This section has presented an overall image of the interlevel communication requirements between the different hierarchical levels and the main controlling logic of the ACPP-EMS controller. A clear image is provided of the information transition between the DNO and controller level on one hand and each community cell under control and the higher ACPP-EMS level on the other.

5.3. Adaptive Community Power Profiler (ACPP)-Energy Management System (EMS)

This section presents an extensive analysis of the algorithmic controller logic. The controller logic blocks are shown in Figure 5.6.

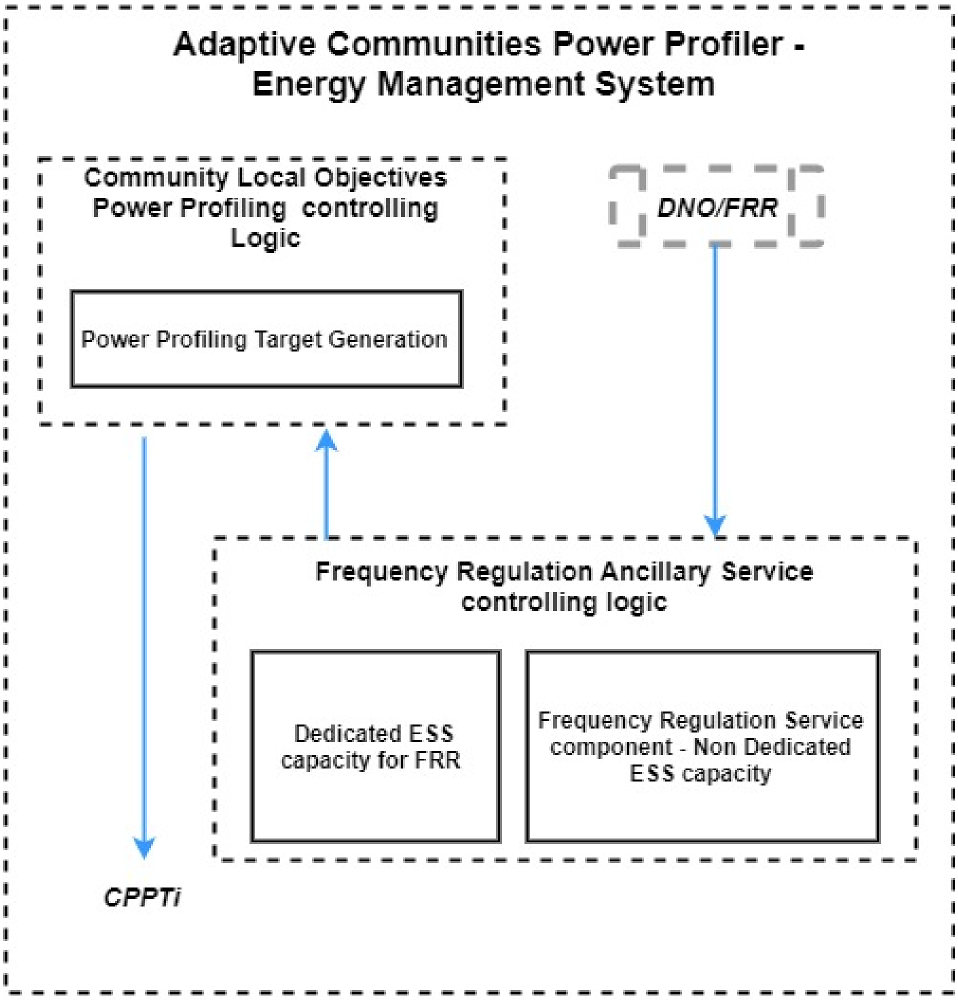


Fig. 5.6 ACPP-EMS controller main controlling logic blocks

As can be observed in Figure 5.6 the controller is divided into two main control logic blocks. The locally generated profiling targets control logic and the frequency regulation ancillary service controlling logic.

The locally generated profiling target logic is responsible for configuring the power profile of the controlling community cells by imposing the generated profiling power targets for the day ahead in order to achieve its main local/community objectives. As stated in previous sections the most important of these objectives are the maximisation of self-consumption of locally generated renewable energy, improved asset utilization by minimising network losses and asset over-loading and the minimisation of energy import during peak demand periods together with associated economic benefit.

To achieve these objectives the profiling targets are generated at midnight before the start of each day and are communicated to the controlled community cell every half hour of the next 24 hours. To generate the targets, a reverse procedure from the end to the start of the day is followed that will be described in the following section.

Although the targets are generated for the controlled community cell 24 hours in advance, they are not dispatched as one block of information, but every half hour for the following half hour time block. The explanation lies in the ancillary services provided framework by the ACPP-EMS as part of the frequency regulation market and for minimising the risk of information loss during communication failures.

When the community cluster controlled by ACPP-EMS is requested to become a frequency regulation service provider, the following half hour profiling target need to be adjusted to meet the DNO requirements. Consequently, all the future targets until the end of the day need to be recalculated.

The frequency regulation ancillary service logic block is enabled and waits for a FRR from the DNO. As long as a regulation request is not made, the community power profiling local objectives block follows its scheduled profiling targets plan calculated before the start of the day. When the DNO communicates and a regulation request is made, the frequency regulation ancillary service logic block alternates the following profiling target to provide the best possible result within the communities' capabilities, At the same time, the community power profiling local objectives block is reactivated to recalculate new profiling targets until the end of the day. Hence it is able to achieve in the best possible way the community objectives for the remaining part of the day under the changed circumstances due to the FRR request.

In addition, in Figure 5.6 can also be observed that the frequency regulation ancillary service logic block is divided further into two sub logic blocks. One is responsible for the part of the ESS that is dedicated to frequency regulation and the other exploits the available capabilities of the community cells for frequency regulation in the most beneficial manner when an FRR is made. A detail presentation of the two sub blocks is given in section 5.3.2

5.3.1 Locally Generated Profiling Targets Controlling Logic

The locally generated profiling target for the controlled community cells is based on a reverse logic that starts from the days end and moves towards the start of the day. This reverse logic was chosen because at the end of each day (24:00) the community ESS capacity should be fully exploited and the system ideally will be completely depleted, since in residential communities the end of the day is after the peak demand period and consequently the expensive price tariff in price tariff schemes available by energy providers [80]. Using the reverse logic, the power profiling target generation procedure is presented in Figure 5.7. Four fundamental time period blocks were chosen since they characterise a typical residential community's demand profiles.

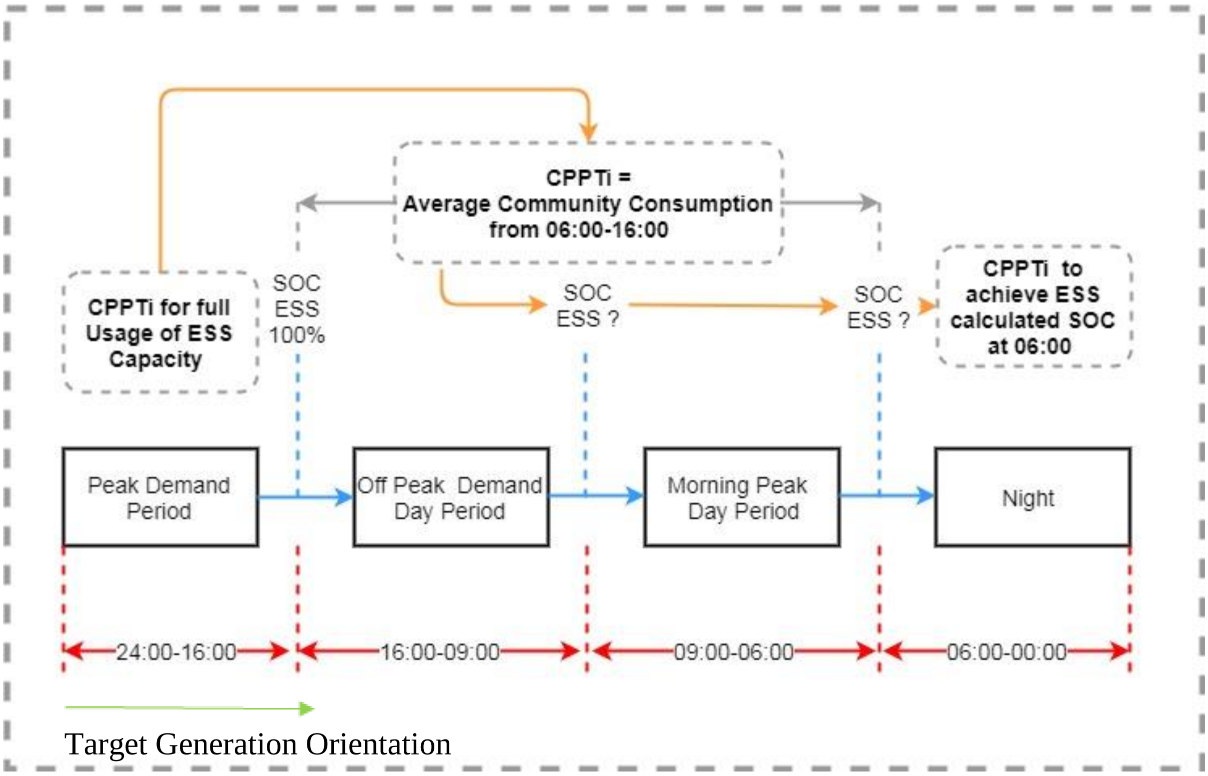


Fig. 5.7 Locally Generated Profiling Targets Controlling Logic

The four fundamental blocks as presented in Figure 5.7 are: the peak demand period starting from 16:00 until 24:00, the off peak day demand period starting from 09:00-16:00 which is at the same time the high PV generations period of local roof mounted photovoltaics, the morning peak time period between 06:00 and 9:00 and finally the night/low demand period from 00:00 until 06:00.

Starting from the peak demand period, it was decided that at the start of the period, 16:00, the aggregated community cell ESS should be fully charged. The decision was made based on the fact that the full available capacity of a community cell ESS should be used during the peak time/expensive tariff period to provide the biggest possible economical benefit to the community cell and at the same time benefit the electrical system by lowering the power demand during this high stress period.

To calculate the *CPPTi* for the 16 half hour blocks in the Peak Demand period an internal control iteration procedure is followed as presented in Figure 5.8. As can be observed, different profiling targets in small descending steps of 100 watts are compared against the forecasted *ERi* . When the calculated SOC of the community ESS is equal or very near to zero at the end of the peak demand period, then the profiling targets are accepted as the most suitable for that fundamental period.

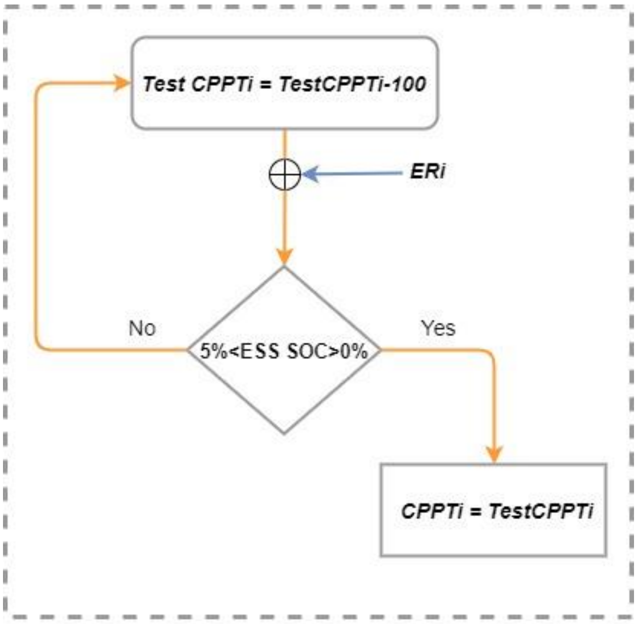


Fig. 5.8 Iteration procedure logic for the calculation of the *CPPTi* during peak demand period

After calculating the profiling targets for the Peak Demand period the procedure moves to the earlier Off Peak Day and Peak Morning Demand periods, as it is shown in Figure 5.7 (orange arrow). These two time periods are combined into one. An overall average demand from 06:00 until 16:00 is calculated based on forecasted values of the *CPPTi* for the included half hour blocks. The reasoning behind that lies in the fact that on the one hand, the Off Peak Day period from 09:00 until 16:00 coincides with the peak locally generated photovoltaic energy period and on the other hand the Morning Peak 06:00-09:00 period requires to reduce the import of energy since this is economically beneficial due to the fact that the Morning Peak period is in the average price zone tariff.

By calculating the average demand for the two fundamental time periods as the community profiling target for that time period we achieve several benefits. For the Off Peak Day period which is simultaneous with the high PV generation period, a higher than demand target leads to the absorption of excess energy generated by PVs locally installed in the controlled community cell, hence maximising self-consumption. Particularly during high PV generation days, community cell demand frequently becomes negative, exporting excess energy to the electrical grid. By forcing the community cell controller to absorb that energy, free of charge energy is acquired to be used later during Peak Demand period.

For the Peak Morning Demand block, a target lower than the demanded power leads to reducing the import energy during the morning peak, hence reducing import during average price tariff. At the same time, by reducing the morning demanded energy, the morning demand peak is flattened and the sudden morning power peaks are reduced as a side benefit for the electrical network.

With the *CPPTi* known between 9:00 and 16:00, the forecasted *ERi* and the need for the SOC of the ESS to be 100% at 16:00 hrs, the required ESS SOC at 09:00 can be calculated. Following the same line of thought, with the SOC at 09:00 known, the ESS SOC at 06:00 can be also calculated. The control logic can be traced with the orange line in Figure 5.7.

Finally, with the SOC known at 06:00 in the morning and the forecasted *ERi*, the *CPPTi* can be calculated for the 12 night half hour blocks using another internal iteration procedure for the night/cheap tariff period very similar to the procedure presented in Figure 5.8. During the iteration, different profiling targets using small ascending steps of 100 watts are compared against the forecasted *ERi*. When the calculated SOC of the community ESS is equal or very near to the required SOC at the end of the Off Peak Night period, then the profiling targets are accepted as the most suitable for night/cheap tariff period.

Following this control logic, devised using the tariff scheme of a cheap night, average of peak day and peak time expensive tariff as presented and compared in Chapter 6, all the stated local objectives can be achieved with excellent results.

5.3.2 Frequency Regulation Services Controlling Logic

In the following sections, the generation logic which adjusts local profiling targets when a Frequency Regulation Request (FRR) is made by the DNO will be introduced.

To make the procedure more transparent and easier to comprehend, the profiling logic during a frequency regulation request is divided into three sub sections in the following analysis. The first two sub sections describe the logical steps for alternating the profiling targets in the half hour block the FR request is made are presented in 5.3.2.1 and 5.3.2.2.

As described in section 5.3, and shown in Figure 5.6, when the DNO communicates and a regulation request is made, the frequency regulation ancillary service logic block alternates the following profiling target to provide the best possible result within the community's capabilities. The frequency regulation ancillary service logic block is divided further into two sub logic blocks. One is responsible for the part of the ESS that is dedicated for frequency regulation and the other to exploit, when it is requested, the available capabilities of the community cells for frequency regulation. The dedicated ESS capacity logic is presented in section 5.3.2.1 and the non-dedicated ESS capacity which is responsible for taking advantage of the available community capabilities for the FR objective is presented in section 5.3.2.2.

The third section presented in 5.3.2.3 is dedicated to the logical steps following the regulation period. Due to the fact that the profiling target during the regulation period is adjusted, the ACPP-EMS local objectives block is reactivated in order to recalculate new profiling targets until the end of the day. By doing so, the ACPP-EMS local objectives block will try achieve the local/community cell objectives for the remainder of the day under the changed circumstances due to the regulation request.

5.3.2.1 Dedicated ESS Capacity for Frequency Regulation Services

Starting with the ACPP-EMS frequency regulation ancillary service dedicated ESS capacity sub-block for FRS, the main control logic is presented in Figure 5.9.

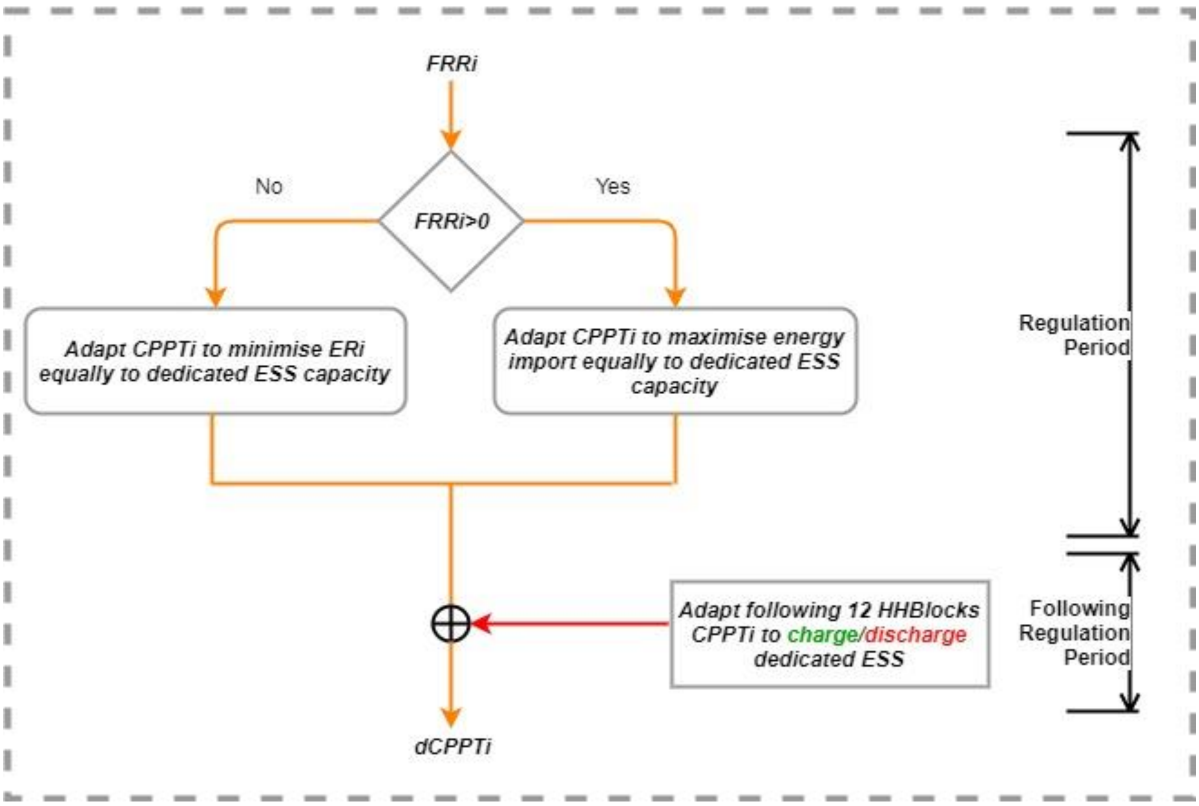


Fig. 5.9 CPPC-EMS frequency regulation ancillary service dedicated ESS capacity sub-block for FRS

This is an easy to understand and straight forward logic since the only duty of the dedicated for frequency regulation services sub-block of the CPPC-EMS controller is to wait for a Frequency Regulation Request (FRR) to be made by the DNO and adjust the CPPT by adding a charging or discharging signal.

As it can be seen in Figure 5.9 when a regulation request (FRRi) is received by the ACPP-EMS from the DNO, the first step is to identify whether the regulation request is to increase demand by charging the dedicated ESS or to provide power to the electrical network by discharging the stored energy in the dedicated capacity of the ESS. This is seen in Figure 5.10 by checking whether the FRRi is higher or lower than 0. In the proposed modelling procedure increasing demand is encoded by FRRi equal to 1 and FRRi equal to -1 to minimise demand respectively.

When the nature of the request is determined, a signal (d*CPPTi*) is sent from the ACPP-EMS to the community cell low level real time controller that is responsible to charge or discharge the dedicated for frequency regulation ESS section for the following frequency regulation 30 minute period.

After the end of the regulation period, as it can be seen by the red arrow in Fig. 5.9, the following 6 hours or 12 Half Hour Blocks (HHB) are used to recharge or re-discharge the used energy due to the regulation request. The 6 hours recovery period after the dedicated frequency regulation period was chosen in order to avoid drastic changes to the community behaviour. If the recovery period following an FRR is small, this can create unexpected peaks or troughs for the community's overall power demand. The recovery period choice is explained in detail in section 6.3.2. To achieve the recharge/re-discharge of the dedicated

ESS the CPPT towards the low level real time controller is adjusted for the next 6 hours by adding a recharging or re-discharging signal (d*CPPTi*).

Obviously due to the nature of the dedicated ESS capacity and due to the fact that no other regulation or local services are provided, the control logic of the system is simple and easily comprehensible.

5.3.2.2 Frequency Regulation Service – Non-Dedicated ESS capacity

The non-dedicated ESS capacity frequency regulation service is responsible for taking advantage of the available community capabilities used locally towards achieving the FR objective. The ESS is normally used by the ACPP-EMS to achieve local objectives as presented in section 5.3.1 but when a FRR is made by the DNO, the ACPP-EMS adapts the scheduled profiling target with the help of the adaptive auxiliary block (TAPM) in order to satisfy the regulation service request with a very high probability rate of achieving the proposed profiling target for the regulation period.

The proposed regulation period profiling target logic when a FRR is made for the non-dedicated ESS frequency regulation capacity is presented in Figure 5.10.

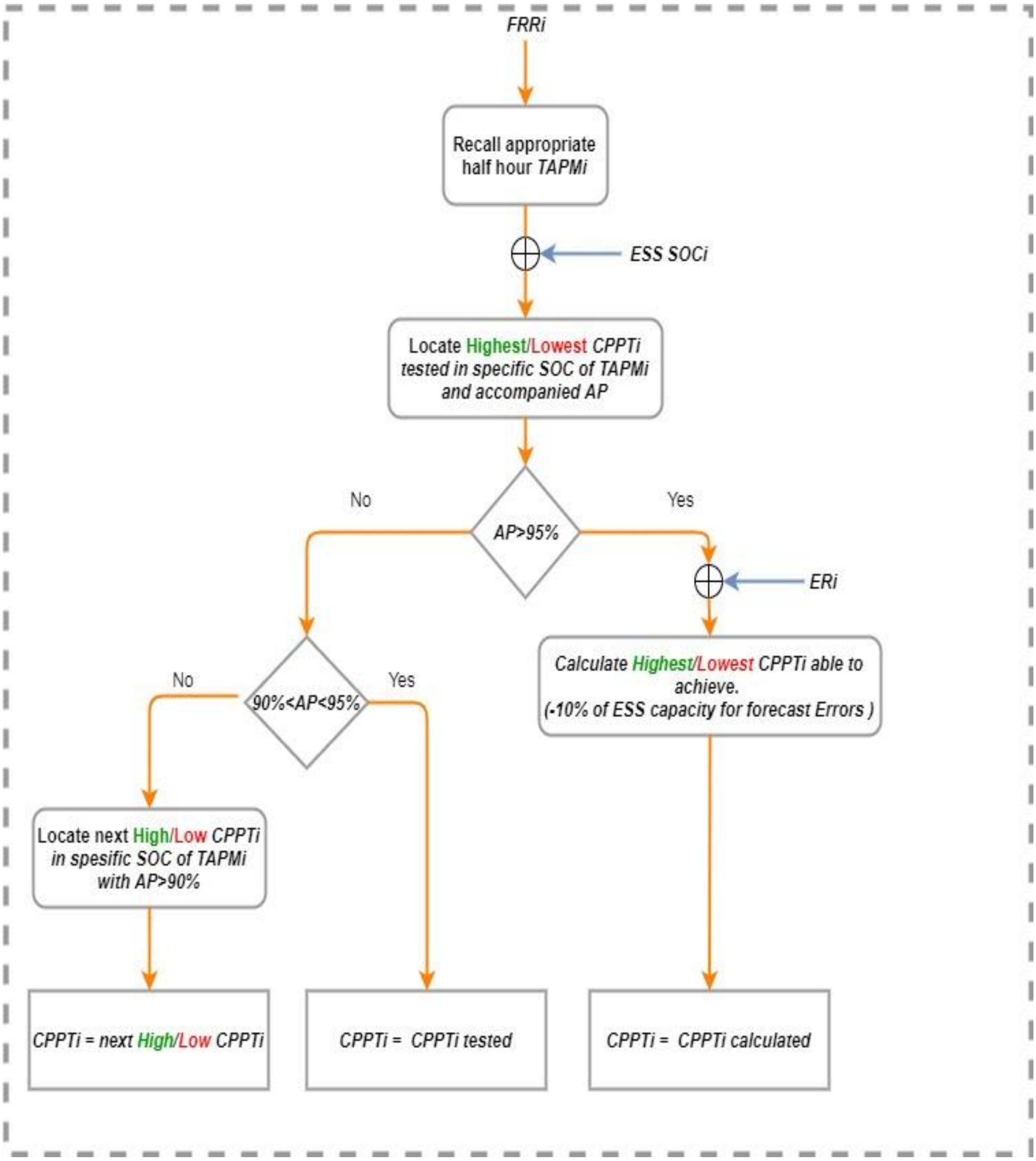


Fig. 5.10 CPPC-EMS frequency regulation ancillary service for non-dedicated ESS capacity sub-block.

As it can be observed in Figure 5.10 when a regulation request (FRRi) is received by the ACPP-EMS from the DNO the first step is to obtain the appropriate half hour cell from the Target Achieved Probability Matrix (TAPMi) using the adaptive auxiliary block. The TAPM of the adaptive block are separated into profiling targets higher or lower than the demand and each element of each matrix of each of the 48 HHB contains the Achieving Probability (AP) of a target for a particular ESS SOC of the community cell.

Once the appropriate TAPMi has been obtained and with the ESS SOC information received from the community cell real time controller, the ACPP-EMS controller is required to determine the highest or lowest tested profiling target at that specific SOC according to the nature of the FRR. If for instance the FRR is for minimising the community's energy request during the regulation period, the logic requires the determination of the lowest tested target for the specific ESS SOCi and the accompanying AP. If the FRR is to maximise energy request the highest tested profiling target must be determined.

After acquiring the AP of the highest/lowest tested CPPTi, the next step is to check how high the success probability of the acquired profiling target is. If the probability is very high (AP>95%) then the target is almost certain to be achieved and the controller can recalculate to see if an even higher or lower profiling target can be achieved. Note that an extra 10% ESS capacity percentage is calculated on top as a failsafe mechanism for possible forecasting errors. After the improved target calculation has been completed the new proposed regulation target (CPPTi calculated) is published to the lower level community cell to follow during the regulation period.

If the acquired AP is between 90% and 95%, the tested profiling target is considered sufficient and able to be achieved with a high probability. A high probability AP is regarded as the best possible target to be imposed to the community cell controller, hence the CPPTi tested is directly published to the lower level community controller.

Finally, if the AP is lower than 90%, the success percentage is considered very low and the control logic requires the discovery of the next higher/lower profiling target from the appropriate TAPM for the specific ESS SOC, that has a probability of success higher than 90% (AP>90%). This is then published to the community cell to be followed during the regulation period. By using a target with high success probability we achieve the security required that the target proposed to the DNO for the regulation period can be achieved without divergence.

By using the auxiliary adaptive block as the base of the presented logic for the non- dedicated ESS block of our ACPP-EMS controller for FRR, the proposed target minimises the chances of errors during the regulation period to very small percentages.

5.3.2.3 Locally Generated Profiling Targets Control after Frequency Regulation

After FR request period which takes advantage of the non-dedicated ESS capacity is finished, the ACPP-EMS needs to reschedule the profiling targets due to the unplanned changes caused by the frequency regulation for the remaining time periods until the end of the day. These new profiling targets are generated as described in section 5.3.1 by the ACPP-EMS local objectives controlling logic to achieve the best possible local/community objectives while taking into account the changes in the community cell due to the FRR period.

The profiling targets rescheduling depends mainly on two important parameters. The first parameter is the fundamental demand period in which the FRR/regulation period is located. For example, a regulation period that occurred during the Night Off Peak (00:00-06:00) fundamental time period will be handled completely differently to a regulation period during the Peak Time (16:00-23:00) fundamental period.

The second important parameter is the nature of the FRR. Minimising or maximising the community's energy request during the regulation period will have a completely different consequence to the community cell available energy resources. Therefore, a different approach is required by the ACPP-EMS controller in order to generate the following time periods profiling targets and obtain the best results in terms of achieving the controller main local objectives.

The rescheduling profiling target procedure followed by the local objectives power profiling block of the ACPP-EMS controller will be presented using four different control logic diagrams for each of the fundamental control time periods the FRR occurred.

5.3.2.3.1 Locally Generated Profiling Targets Control after Frequency Regulation during the Night Off Peak Fundamental Period

Starting from a rescheduled power profiling target for an overnight FRR/regulation period the control logic is presented in Figure 5.11.

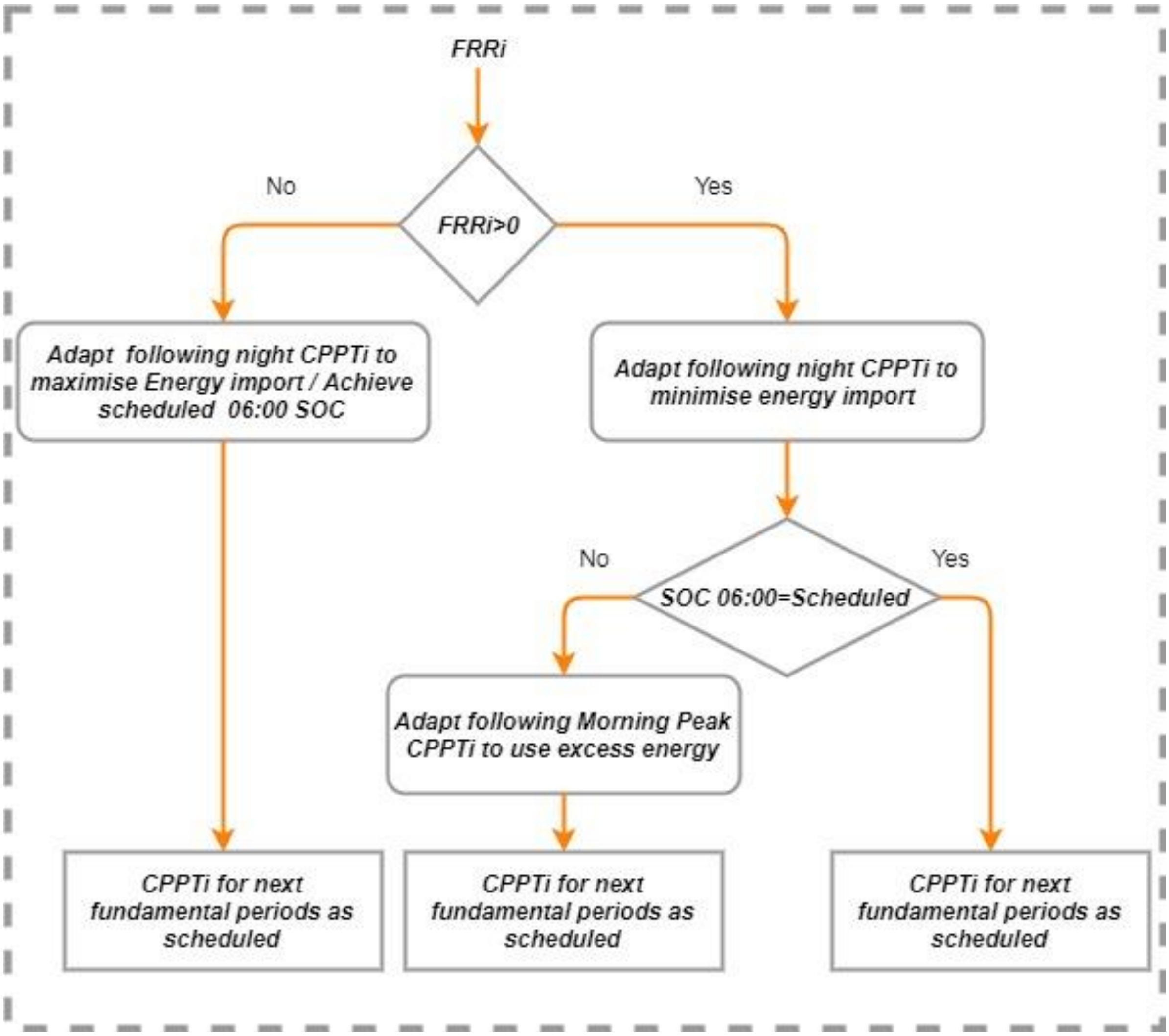


Fig. 5.11 CPPC-EMS rescheduled power profiling target logic for a night (00:00-06:00) FRR/regulation period

As it can be seen in Figure 5.11, after the FRR is identified between increasing demand, encoded with FRRi equal to 1 or FRRi equal to -1 to minimise demand respectively and the regulation period logic presented in the previous paragraph is executed, the subsequent overnight CPPTi should be adapted/recalculated based on the nature of the FRR. At this point and the action required to be made for the FRR is known.

If during the FRR period the demand was increased (FRRi equal to 1), the energy import for the following HHB of the Night Off Peak fundamental period should be minimised in order to try and achieve the predefined SOC for the ESS of the community cell at the end of the nigh fundamental period (06:00) as scheduled before the FR request. The reasoning behind this decision is firstly to minimise any extra energy import during the night time period for charging the ESS and, by doing that, avoid the overnight energy charges since the ESS is already charged more than planned. More importantly the ACPP-EMS controller should not overcharge the community cell ESS so that it can to absorb the forecasted locally generated (PV) renewable energy, during the subsequent day time fundamental periods.

Following the logic diagram of Fig. 5.11 if the ESS SOC at the community cell at the end of the Nigh Off Peak fundamental period (06:00) is equal to the value scheduled before the regulation request. The implementation of the new adapted/recalculated nigh CPPTi targets was enough and the subsequent fundamental periods follow the original scheduled CPPTi targets until the end of the day.

If the SOC value differs from the scheduled value, the subsequent Morning Peak time period must also be adapted/recalculated to use the excess overnight energy by further minimising the morning peak community cell demand. In this manner the morning peak is pulled even lower, saving extra energy import during the morning peak and at the same time keeping the self-consumption target unchanged. For the subsequent Off Peak Day and Peak Time fundamental periods the profiling targets remain as scheduled before the FRR.

Finally, if during the FRR period the demand is minimised (FRRi request equal to -1), the subsequent Night Off Peak CPPTi profiling targets are adapted/recalculated to achieve the scheduled community cell aggregated ESS SOC at the end of night (06:00). The Nigh Off Peak fundamental period is ideal for maximising energy demand since night energy tariff is the cheapest available and at the same time the overall community demand is at its lowest.

The subsequent CPPTi targets remain as scheduled before the FRR for the remaining fundamental periods.

5.3.2.3.2 Locally Generated Profiling Targets Control after Frequency Regulation during the Peak Morning Fundamental Period

The second control logic diagram presented in Figure 5.12 is for a FRR during the Peak Morning (06:00-09:00) fundamental period. As it can be seen in Figure 5.12, after the FRR is identified, the following Peak Day CPPTi is adapted/recalculated depending on the nature of the FRR request.

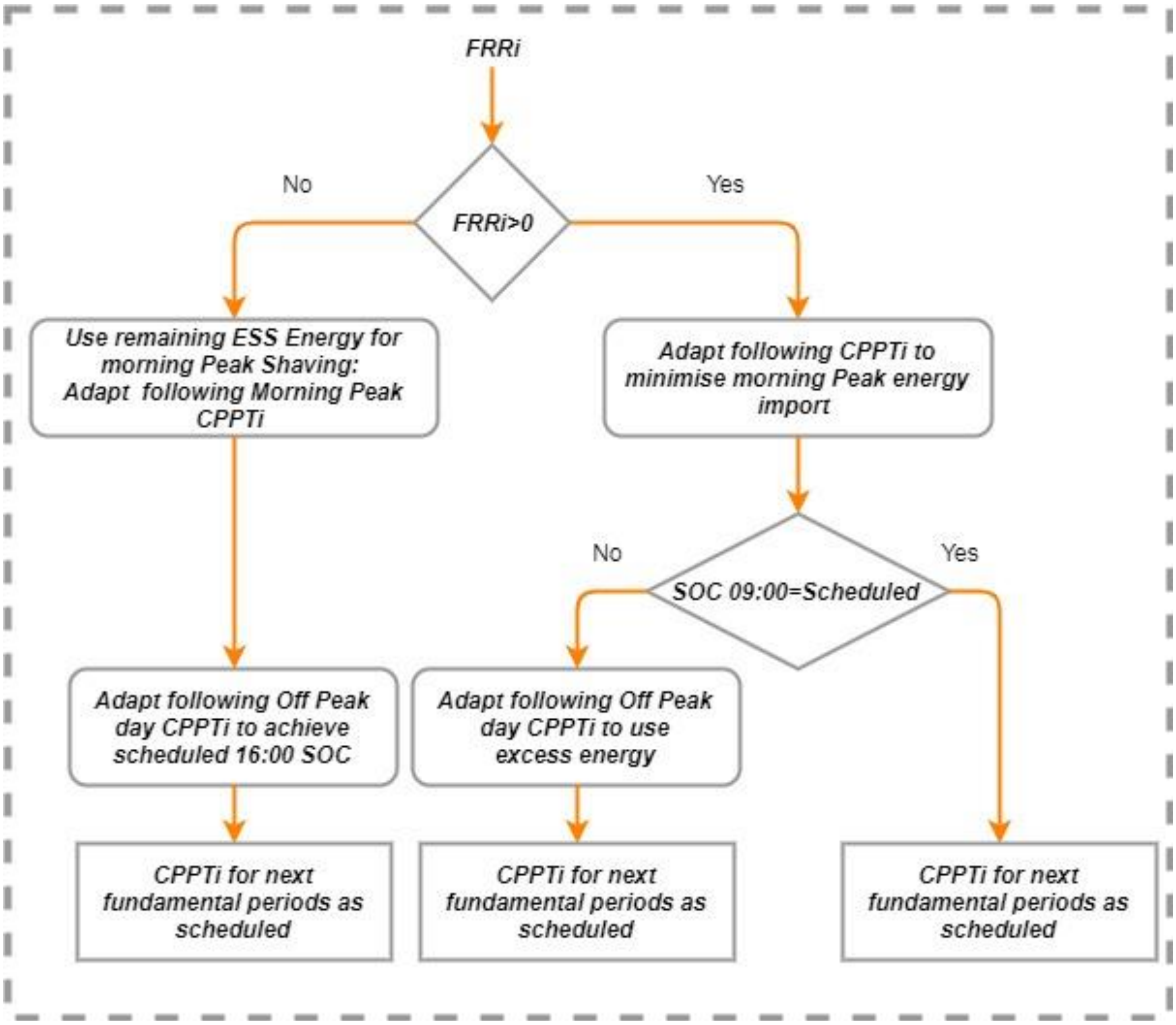


Fig. 5.12 CPPC-EMS rescheduled power profiling target logic for a peak morning (06:00-09:00) FRR/regulation period.

If the FRR/regulation period is for maximising energy demand, the subsequent Peak Demand CPPTi profiling targets are adapted to minimise the morning peak energy import to achieve the scheduled community cell ESS SOC at the end (09:00) of this fundamental period. The stated logic is followed to minimise the import required by the community energy during the morning peak and consequently reduce the import energy cost. At the same time the ACPP-EMS controller by adapting the CPPTi profiling targets avoids overcharging the community cell ESS and making it not able to absorb locally generated (PV) renewable energy during subsequent fundamental periods.

If achieving the scheduled ESS SOC at the end of the Morning Peak period (09:00) is not possible, the already low due to local generation Off Peak Day fundamental period (06:00-16:00) demand CPPTi targets, are adapted (if possible) to minimise demand during these half hour blocks whent the import energy reduction is possible. The subsequent Peak Time fundamental period follows the scheduled CPPTi targets.

If the FRR request and period is to minimise demand (FRR=-1), the subsequent Morning Peak time CPPTi are adapted to use any remaining ESS energy for shaving the morning peak import if possible. The subsequent Off Peak Day fundamental period (09:00-16:00) is used to recharge the community cell ESS to its predefined SOC before the start of the Peak Time period. The CPPTi are now adapted to import the required energy from the electrical network and at the same time absorb all the locally generated (PV) energy in order to fully charge the ES system. The CPPTi profiling targets at the following Peak Time fundamental period are as scheduled at the start of the day.

5.3.2.3.3 Locally Generated Profiling Targets Control after Frequency Regulation during the Off Peak Day Fundamental Period

The third control logic diagram presented in Figure 5.13 is for a FRR/regulation period during the Off Peak Day (09:00-16:00) fundamental period. The logic followed as presented in the 5.13 Figure starts as the previously presented regulation period diagrams, by distinguishing the nature of the FRR/regulation period between increasing demand or minimising demand.

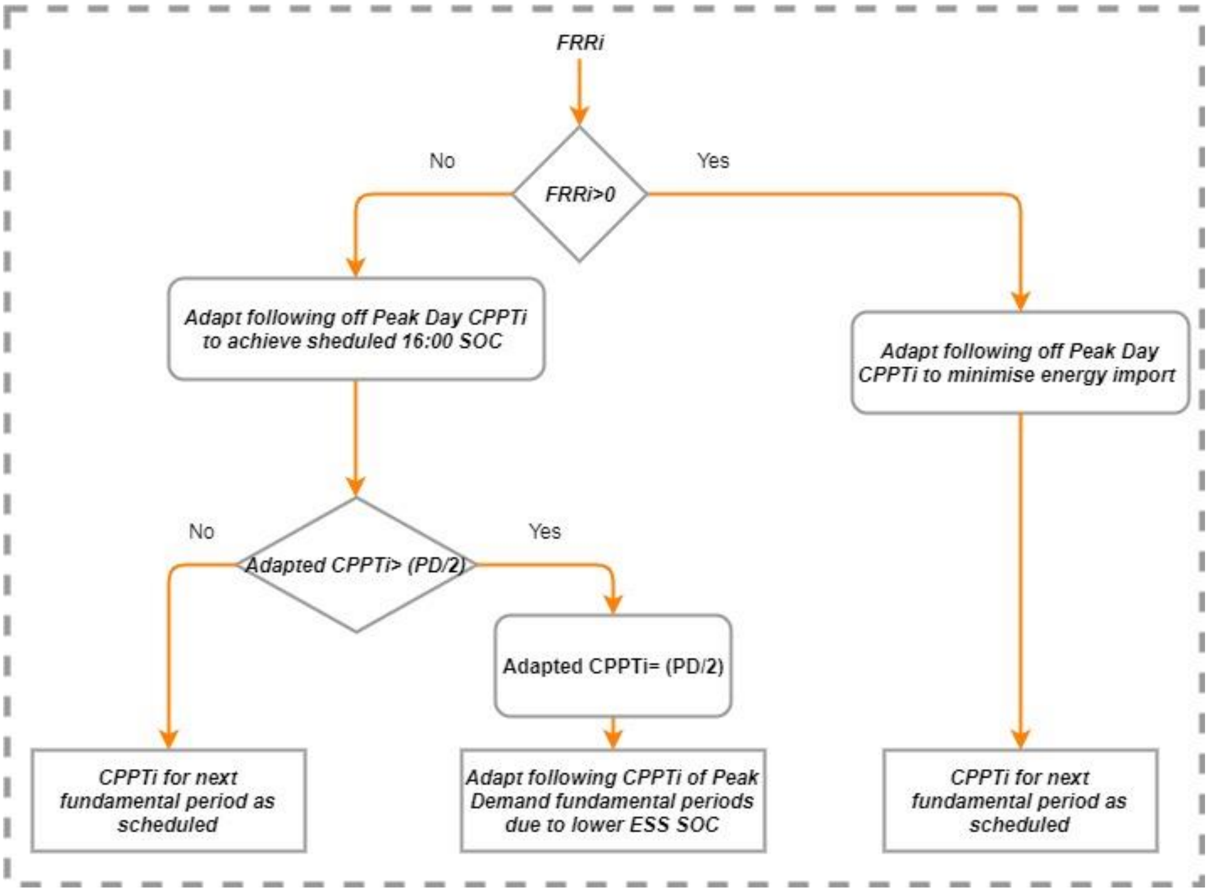


Fig. 5.13 CPPC-EMS rescheduled power profiling target logic for off peak day (09:00-16:00) FRR/regulation period.

If during the regulation period the community energy import was increased, the ACPP-EMS controller adapts the following CPPTi to minimise energy import for the following HHB until the end (16:00) of the Off Peak Day demand fundamental period and at the same time absorb all the locally generated (PV) renewable generation. During the subsequent Peak Demand fundamental period the ACPP-EMS controller follows the scheduled CPPTi targets without the need for any profiling target adaptation.

On the other hand as presented in Figure 5.13, if during the FRR/regulation period the energy import was minimised, the subsequent of Peak Day profiling targets need to be adapted in order to achieve the predefined community cell ESS SOC at the end of the period (16:00). If the FRR period occurs towards the end of the Off Peak Day fundamental period the adapted targets by the ACPP-EMSS might get disproportionally high when compared to the overall Off Peak fundamental period demand and therefore a limitation should be imposed. For instance if a FRR to minimise energy demand occurred from 15:00-15:30, the following single HHB until the end of the Off Peak Day fundamental period the adapted CPPTi target generated by the ACPP-EMS is required to reabsorb the energy loss completely. This leads to a very high adapted target following the regulation period.

In order to avoid this situation the imposed limit of the adapted/recalculated target is set as half of the forecasted community cell Peak Demand (PD). If the adapted targets (CPPTi) by the ACPP-EMS following the regulation period are lower than the imposed limitation (Adapted CPPTi<(PD/2)), the following Peak Day demand period scheduled targets remain unchanged.

If the adapted/recalculated Off Peak fundamental CPPTi profiling targets generated by the ACPP-EMS are above the limit, they are limited to be equal to the imposed limit (Adapted CPPTi=(PD/2)) and the following Peak Time fundamental period CPPTi targets are also adapted to be higher as a result of the lower community cell ESS energy available.

5.3.2.3.4 Locally Generated Profiling Targets Control after Frequency Regulation during the Peak Day Fundamental Period

The final and simplest of the adapted/recalculated logic is for a FRR that occurs during the Peak Day demand (16:00-23:00) fundamental period. The logic is presented in Figure 5.14. The first step is to distinguish between maximising or minimising the energy import in the FRR regulation period.

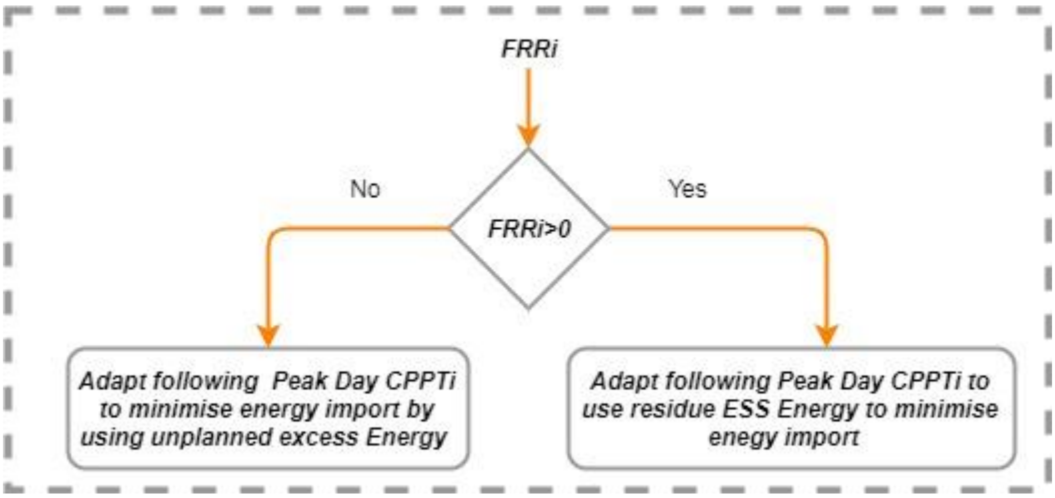


Fig. 5.14 CPPC-EMS rescheduled power profiling target logic for Peak Day (16:00-23:00) FRR/regulation period.

If during the regulation period the energy import was maximised, the following CPPTi targets generated by the ACPP-EMS are adapted in order to minimise the energy import by using the unexpected excess energy from the regulation period. The new adapted/rescheduled following targets are lower than the originally scheduled targets and the import power demand becomes lower during the Peak Day demand fundamental period.

If the energy import was minimised during the FRR period, the unused community ESS energy is used to minimise energy import as much as possible by adapting the ACPP-EMS following targets higher. Using the community cell energy capabilities for frequency regulation instead of peak shaving during the peak demand period is preferred since it is more economically beneficial for the community cell. The FR tariff is much higher compared to the expensive peak time period energy import tariff and is always preferred when a FRR is made by the DNO.

5.4 Conclusion

This chapter presents a step by step description of the CPPC-EMS higher level controller capabilities and control logic.

In the first section all the necessary auxiliary service blocks and the required communications were presented in order for the controller to be able to fulfil its main objectives. The presented auxiliary blocks are used to provide vital information to the main control logic. How the information is captured/calculated and how it will be used by the main controlling logic was also presented and analysed.

In the second section the main CPPC-EMS controller logic was divided into two fundamental blocks, each one responsible to providing different services to fulfil different objectives. In section 5.3.1 a clear and transparent picture was presented of the logic approach for the generation of the locally generated profiling targets for each of the controlled community cells. The locally generated profiling target logic is responsible for the power profile of the community cells by imposing the generated profiling power targets for the day ahead in order to achieve their main local/community objectives.

In Section 5.3.2 the proposed novel ancillary services provided be the ACPP-EMS as part of the frequency regulation market was presented. The frequency ancillary service is divided into two major sub-blocks for the “dedicated” and “non-dedicated” ESS frequency regulation capacity available in the community cell. The logic for each of the two sub-blocks was analysed when frequency support is requested by the DNO level. For the non-dedicated ESS for frequency regulation, a description of how the frequency regulation ancillary service logic part of the ACPP-EMS controller alternates the subsequent profiling target to provide the best possible result within the communities’ capabilities is analysed. Furthermore the importance of using the novel adaptive block to achieve the regulation service CPPTi profiling target with high probabilities in the control logic is stressed.

Finally, a thorough presentation of the logic of the ACPP-EMS for the CPPTi following an FRR period until the end of the day is made. The subsequent CPPTi should be adapted/recalculated in order to achieve in best possible manner the community objectives for the remainder of the day under the changed circumstances. For every scenario the ACPP-EMS can face, a logic to be followed is displayed.

Overall each of the chapter sections provides a clear, transparent and detailed presentation of the procedural logic behind each of the control decisions taken by the Adaptive CPP-EMS.

Chapter 6: Simulation Scenarios, Results and Analysis

6.1 Introduction

Having presented the development of the higher level ACPP-EMS controller in chapter 5, this chapter will present the results obtained through the implementation of the controller in different simulation scenarios. The simulation results will be presented in four different parts in section 6.3 where the abilities of the controller will be gradually presented and the benefits from its usage will be quantified.

In the first part the ability of the ACPP-EMS controller for achieving its declared objective for the controlling area will be analysed and presented through its profiling power target generation mode. The controller at this stage is not considered part of the frequency regulation market and is in “power targets only generation” mode, where it is generating power flow targets for the controlled community. In this mode the ACPP-EMS is responsible for generating power flow targets for the lower level real time community controller.

When the ability of the controller to efficiently generate profiling power flow targets for the lower real time controller is established, a proposed new regulation service will be introduced. The ACPP-EMS controller at this stage will also be considered to be part of the frequency regulation market. With the regulation part also enabled, the controller will be responsible to generate power flow targets for the controlled community as seen in the previous section and at the same time become part of the regulation market mechanism. Through this new regulation service the ability to provide greater benefit will presented.

Following the extra benefit gains from the frequency regulation market, an economic analysis for the payback period of the installed ESS is introduced, in order to quantify the benefit acquired by the combined use of the two parts of the ACPP-EMS controller.

Finally, the impact of introducing a more sophisticated lower level real time controller at the community cell level of the hierarchical structure is examined. By adding Demand Side Management capabilities, the hypothesis that a more advanced low level real time controller can improve the results even further is studied

A detailed analysis and thorough analysis of the above is presented in the following sections

6.2 Simulation Results - Simulation Methodology

In order to demonstrate the effectiveness of the proposed ACPP-EMS a number of scenarios will be gradually introduced, where the abilities of the controller will be presented and different parameters will be tested. The community used in the simulations is constructed around the models developed in Chapter 4 and represents a typical current and near future urban community.

The main structure of the community comprises of 100 dwellings with each one of them containing all the major and most common household appliances. 100% of the dwellings include a fridge freezer, washer dryer, electrical hob and oven, microwave and a TV. Furthermore, in order to achieve a more realistic result for the model community, the occupant's number is not constant for all dwellings but varies between 2 and 5 occupants. The penetration levels of the PV systems, the EVs and the capacity of the ESS in the communities will be varied according to the scenario studied. Each residential roof mounted

PV system is considered to be a 3kWp system as an average size of household PV system typically encountered in the UK. Each EV as described in chapter 4 charges with a power of 3 KW and the nominal battery capacity is equal to 18.7 kWh.

The simulation time step size is 1 minute and the ACPP-EMS generate community targets every 30 minutes. Each day is divided in 48 Half Hour Blocks (HHB) and the targets generated are published and executed in 30-minute time segments.

6.2.1 Comparison of ACPP-EMS Controller in Profiling Power Target generation mode

The first simulated scenario is used to show the effectiveness of the controller in comparison with commonly used controlling logics. The controller at this stage is not considered part of the frequency regulation market and is in "power target only generation" mode, where it is generating power flow targets for the controlled community. In this mode the ACPP-EMS is responsible to generate power flow targets for the lower level real time community controller following the procedure described in Chapter 5.

The community cell, used for the comparison, consist of 100 dwellings. 50 electric vehicles are also considered to be part of the community cell structure. The 50% EV penetration is considered a realistic future scenario since according to estimations 25% of the PEVs will account to 25% of the total automobile sales by 2020 [16]. The EVs start charging when they return home and are plugged in without any type of control. During the simulation the real time power flow controller at the lower level controls only the community battery controller sub function as described in chapter 4. The total installed capacity of the roof mounted PV systems is equal to 120 kWp (40% penetration) and the aggregated community BESS capacity is equal to 350 kWh. The 40% PV penetration although at first can be considered high, it can also be assumed to be a realistic future community level scenario since according to estimations presented by Gardner et. al [3] for national grid, until 2035/2036 renewable generation in some scenarios will be providing up 50% of the total generated energy. Finally, the 350 kWh capacity of the BESS is also calculated according to the energy storage system methodology presented in chapter 4.

The comparison is made between the main controlling procedures as they are described by the most eminent residential battery ESS producers [9, 10, 11]. A constant target set for each day, equal to the average predicted community power demand, set as a reference target by a higher hierarchical level [25]. The stated constant reference target for the lower level real time controller is used in the comparison since is considered a logical approach to achieve commonly encountered local objectives such as energy shifting during high demand periods, night charging and general energy usage cost reduction. The schemes listed above are compared with the variable target generated by the proposed ACPP-EMS higher level controller and used a reference target for the lower level real time community controller.

According to the “greedy” control scheme [9, 10, 11], when the battery energy system is combined with PVs, the suggested strategy as described by the producers of the ES system is to either absorb and store surplus energy that is generated by the PV system and not used for their own consumption or store all the PV generated energy when is generated. The stored energy is used in the afternoon during the expensive tariff /peak demand period. The two control approaches are coded as PVF1 and PVF2 accordingly.

Furthermore, the real time power flow controller can either follow a constant power flow target [25], equal to the yearly average power demand or if the community controller is part of a hierarchical structure, as in the framework proposed in the current work, follow a power flow target generated by the higher-level hierarchical structure. The constant power flow target in the following comparison is coded as CPT1.

Accordingly, the proposed in Chapter 5, higher level ACPP-EMS controller reference target to be followed by the lower level real time controller, is coded as CPT2. As described the ACPP-EMS is responsible for generating variable power flow targets to be used as reference targets by the community cell community controller in order to achieve its local objectives.

For simplicity and efficiency, the simulation process performed at community/cell level the small individual energy storage systems can be considered, from a higher hierarchical level point of view as a single BESS with capacity equal to the aggregated capacity of the individual residential energy storage systems. The community cell is controlled by the lower level real time power flow controller described in chapter 4.

6.2.1.1 Comparison Indicators

Obviously in order to compare the different controlling methodologies a number of different indicators need to be employed and explained. The first Indicator used for the comparison is the Energy Import (E_I) during the simulated period.

$$\mathrm{E_I} = \frac{\int_0^t \mathrm{P_{imp}}}{(1000*60)} \quad (6.1)$$

The E_I indicators is equal to the aggregated energy imported throughout the simulation period for the given community and it is given in KWh. $\mathrm{P_{imp}}$ is the imported power from the grid at every step of the simulation period. A second important energy import indicator is the energy import only during the peak demand/peak tariff time period. As the peak time period is considered to be the time period between 16:00 hrs until 23:00 hrs every day, the Peak Time Energy Import is given by (6.2).

$$E_{IPT} = \frac{\sum_{1}^{Day} \int_{16:00}^{23:00} P_{imp}}{(1000*60)} \quad (6.2)$$

The overall energy import when compared with the import of energy during peak time, can give a rough idea of the overall utilisation of locally produced energy and at the same time the impact of the control strategy during peak time period.

A third indicator is the cost of import energy during the simulation period, through the indicator it can be observed how the cost is modified by the followed control technique. For the cost calculation a currently available tariff scheme from Green Energy UK TIDE [80] was used. According to the TIDE tariff scheme implemented by Green Energy UK the different tariffs, for each tide, are presented in table 6.1 and the energy import cost (C_{EI}) is calculated using (6.3).

Table 6.1 TIDE tariff scheme

Name of Tariff	Applied Time Period	Cost (pence/KWh)
Cheap Night Tariff/Low Tide	23:00-06:00	4.99
Normal Day/Tide	[06:00-16:00] [23:00-24:00]	11.99
Expensive Day/High Tide	16:00-23:00	24.99

$$C_{EI} = \left[\frac{\sum_{1}^{\mathrm{Day}} \int_{16:00}^{23:00} \mathrm{P_{imp}}}{(1000*60)}\right] * Expensive_{\,D} + \left[\frac{\sum_{1}^{\mathrm{Day}} \int_{06:00}^{16:00} \mathrm{P_{imp}}}{(1000*60)}\right] * \ Normal_{D} \ +$$

$$\left[\frac{\sum_{1}^{\mathrm{Day}} \int_{23:00}^{24:00} \mathrm{P_{imp}}}{(1000*60)}\right] * \ Normal_{D} + \left[\frac{\sum_{1}^{\mathrm{Day}} \int_{24:00}^{06:00} \mathrm{P_{imp}}}{(1000*60)}\right] * \ Cheap_{N} \quad (6.3)$$

Where the total cost of import energy for the simulation period (C_{EI}) is calculated by multiplying the import energy during each tariff period with the corresponding price tariff. $Expensive_{\,D}$, $Normal_{D}$ and $Cheap_{N}$ are the expensive, normal and cheap tariff respectively.

Another important indicator for understanding the behaviour of our control framework is the energy export. The energy exported from the community is calculated during the whole simulated period. If self-consumption is considered an important objective for the control scheme, then Energy Export (E_e) can give a clear picture of that parameter for comparison purposes. The total energy exported can be calculated according to (6.4).

$$E_e = \begin{cases} \frac{\int_0^{t}(-\mathrm{P_{imp}})}{(1000*60)} & \mathrm{P_{imp}}<0 \\ 0 & \mathrm{P_{imp}}>0 \end{cases} \quad (6.4)$$

Where $\mathrm{P_{imp}}>0$ is the importing power and $\mathrm{P_{imp}}<0$ is the exporting power from the community cell.

The final indicator proposed is used to provide information of how often the energy storage system is in operation and its full capacity is used. In order to quantify that information, the

Equivalent Cycles (EC) calculation throughout the duration of the simulation was used. The EC as can be seen in (6.5) is the total energy discharged from the ESS divided by the capacity of the system itself. The discharged energy is used in this case but the charge energy of the system could be used with similar results. One energy storage system equivalent cycle is equal to the energy required for full charging and discharging of the system. Under the assumption that the charging energy is equal to the discharging energy, the Energy Storage System Equivalent Cycles (ESS_{EC}) is calculated according to (6.5). The BESS losses are neglected since they do not to affect the comparison results.

$$ESS_{EC} = \frac{\left[\frac{\int_0^{t}(-P_{disch})}{(1000*60)}\right]}{ESS_C} \qquad P_{disch}<0 \quad (6.5)$$

Where P_{disch} is equal to the discharge power from the energy storage system and ESS_C is the capacity in KWh of the system in discussion.

The presented indicators will be used for the comparison of the impact of each control scheme in the following sections.

6.2.1.2 Comparison results

As described above the comparison for this first stage of variable target generation without the frequency regulation part of the ACPP-EMS controller is between four different control strategies. Firstly, we have the two control strategies as they are described by the storage system manufacturers when working with photovoltaics. According to what is proposed, the storage systems can either absorb all the energy produced from the PVs and use it during the evening/peak time period (scheme PVF1) or absorb only the excess energy that is not used for own consumption and similarly use it during the evening peak time period (scheme PVF2). In this case the lower level real time community controller is not responsible for following any target from a higher level but follows the power generation of the PVs in the community and charges or discharges the battery ESS accordingly.

In the third and the fourth control strategies, targets are provided from the higher hierarchical level to the community real time controller. The real time controller follows the given target. In the third simulated scenario the higher-level target is constant and equal to the predicted average community power demand for the year (CPT1). In the fourth simulation scenario for comparison, the target is variable and is generated from the proposed ACPP-EMS controller following the control procedure described in Chapter 5 (CPT2). The simulation period is equal to one Year (365 days).

Starting the comparison, the two first indicators to be used are energy import and energy import during peak time period and are presented in figure 6.1.

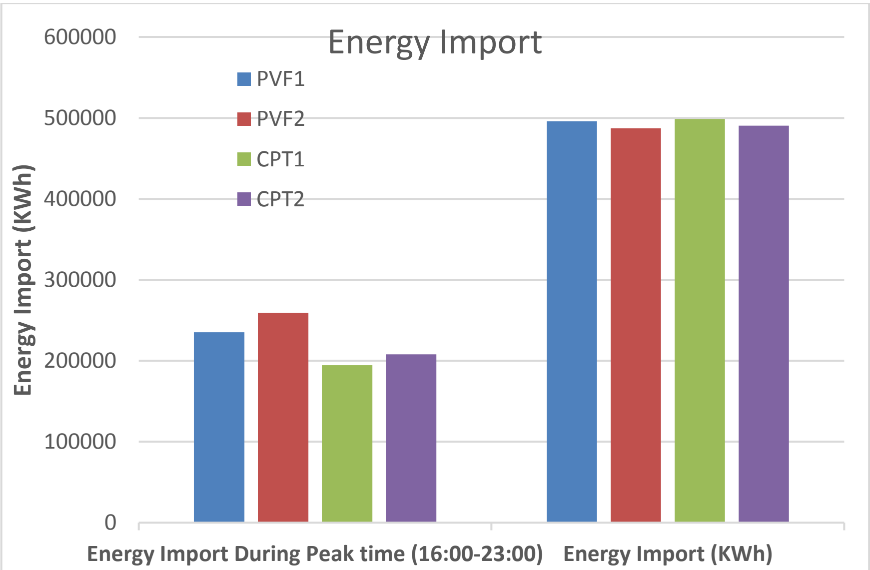


Fig 6.1 Energy Import and Energy Import during peak time period for the four simulations under comparison.

As it can be seen from the Fig 6.1 (right) the overall energy import in all the compared strategies is very similar. That is expected as the overall energy of the community demand does not change with the control strategy used. The control strategy is able to change, by shifting the energy demand from one time period to the next, the energy demand in specific time periods. The slightly lower overall demand when using PVF2 and when the target is variable (CPT2) is the result of minimising the export of energy from PVs and using it locally leading to a smaller overall need for energy import. The export of energy from the community will be analysed later.

The major difference is the energy import during the peak time period. As it can be seen in Fig 6.1(left) the highest amount of energy import during peak time period exists when using PVF2 followed by the ESS being charge from the total PV generated energy (PVF1) and use it during the peak time period. The PV generation, total or excess generated energy, cannot cover the energy requirements of the community during the peak time period. This becomes worse during the winter period when the PV generation reduces significantly. The two lowest, with a small compared to the two “PV following“ schemes but noticeable difference over the whole year, in actual energy import are the CPT1 and the CPT2 reference targets followed by the community real time controller. This small difference in the import energy during peak time period in the two exists due to the fact that with the constant target the ESS is always fully discharged during the peak demand period in comparison with the variable target that, due to the fact that is based on demand and generation forecasts, might not fully use its stored energy because of forecast errors.

The import of energy during peak time also affects the total cost of the community energy import. The peak time period tariff is the most expensive tariff period. As presented in table 6.1, the expensive tariff is more than double the price of normal day tariff and five times the price of night/cheap tariff. When comparing the cost of import energy in figure 6.2, the difference in the cost of import energy between “following PV generation” control strategies and the higher-level target schemes is very large.

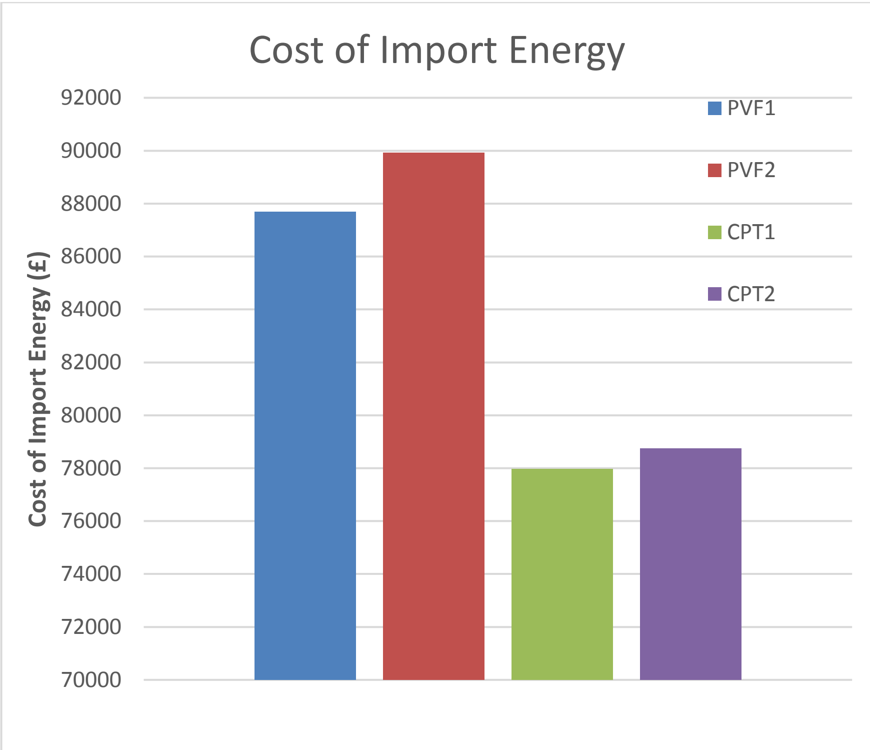


Fig 6.2 Yearly Cost of Energy Import

The highest cost is given by using PVF2 control scheme. The cost is almost equal to 90000 £ per year. Followed with a small difference, when compared with CPT1 and CPT2, by the control logic of PVF1 with a difference of about £3000. A real improvement in the cost of import energy happens with the hierarchical control logic, following the higher-level targets with savings up to £12000 per year. The difference between the constant and variable target cost is £700 which can be considered insignificant.

Although the difference in cost between the two is very small, there is an interesting difference in the behaviour of the constant (CPT1) and variable (CPT2) target when compared with the difference in energy import during peak time period. The difference between the energy import during peak time period between CPT1 and CPT2 is around 10000 kWh per year. At the expensive tariff price (24.99 pence) per kWh during peak time period that would amount to a difference of almost £2500. On the contrary as it can be observed in Figure 6.2 the difference between the two is negligible. The explanation lays in the utilisation of the energy generated locally by the PV systems.

As it can be seen in Fig 6.3 due to the fact that a constant average reference target is followed by CPT1, that leads to fully charging the ESS during night time period, thus resulting in not been able to absorb any excess energy from PV systems during the day. As a consequence locally generated energy is not utilised and thereby exporting it back to the electrical grid. On the other hand, the ACPP-EMS variable target control logic tries and achieves to utilise most of the locally produced energy and thus saving money for not importing energy for the charging of the energy storage system overnight, but instead using the free locally generated energy when this is available.

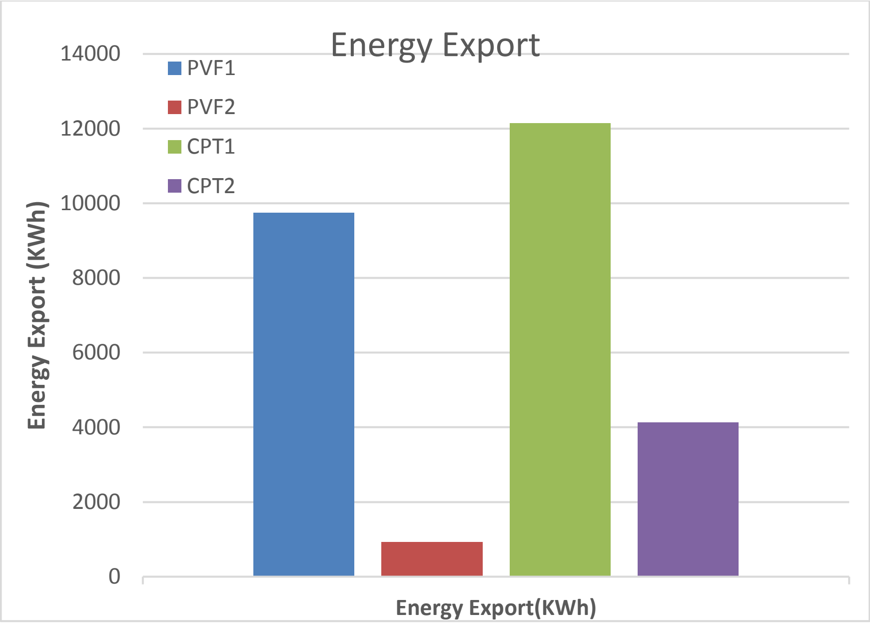


Fig 6.3 Yearly Energy Export

The variable target minimises the export of energy compared to the constant target by 66%. Of course, in terms of minimising exporting energy, the best control logic is clearly the logic of using all the excess locally generated energy for charging the ESS. However, although it would be expected that trying to utilise all the PV generated for charging the ESS (blue column) it would have given similar results with employing only the excess energy (red column) that is not the case.

The explanation can be given in a simple example. As stated at the start of the section, the aggregated total generation capability of the PV systems is equal to 120 kW. On a sunny summer day it is assumed that the average generation of the system is 80 kW and that lasts roughly from 09:00 hrs until 17:00 hrs that will be an energy generation yield of 640 kWh. Although the previous example is simplistic it shows that, mostly during the summer period, the ESS capacity can be significantly smaller than the actual generated energy. With a simplistic ESS controller just responsible for absorbing the generated energy and charging the

ESS, when that is full, any excess generated energy will be exported back to the electricity grid.

Finally minimising the export energy does not necessarily mean that the full available capacity of the ESS is exploited. An analysis of the capacity usage of the storage systems installed inside the community can be made by using the equivalent cycles (EC). By calculating the equivalent cycles of the energy storage system we can get an understanding of how much of the aggregated capacity of the system was utilised by each controlling logic.

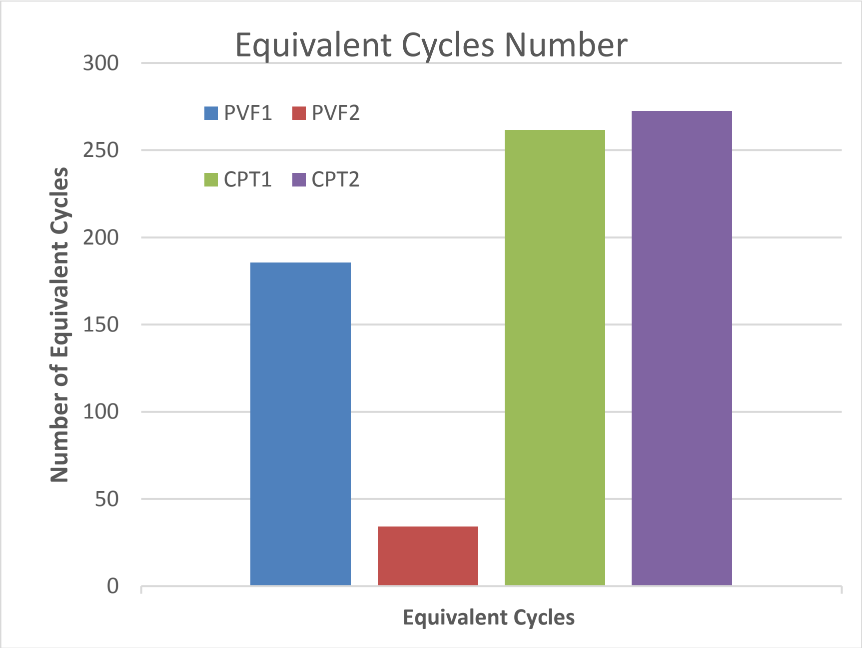


Fig 6.4 Equivalent Cycles number over 1 Year

As can be observed in Figure 6.4, when the ESS is charged only from excess PV generation (PVF2) the ESS is barely used. If the total PV generation (PVF1) is used for charging the ESS, the difference as expected is significant. The better control logics in terms of EC are given by the CPT1 and CPT2 target with the latter having the best result. Due to the fact that the proposed controller, functions on a next day (24 hrs) planning horizon. The best results in terms of EC are considered to be from a control scheme that is able to exploit most the full capacity of the ESS per day.

The difference between the two is slightly more than eleven EC. The difference can be explained by the fact that the variable (CPT2) higher-level target due to its nature forces the real time controller to charge and discharge the ESS more often throughout the day. For instance, the ACPP-EMS, creates low targets in the morning to shave the morning peak existing in residential communities resulting in forcing the real time controller to slightly discharge the ESS. Furthermore, due to the ACPP-EMS objective of maximisation of self-consumption, the targets during the days of high PV generation are created in such a way to force the community controller to absorb the excess energy and recharge the ESS.

Although the above indicators can clearly show that a huge advantage exists in favour of the lower level real time controller to follow a higher level target as they are presented in the previous section, the advantage of the variable target generated by the ACPP-EMS controller (CPT2) over the average demand (CPT1), constant target is not so obvious. The total cost of import energy is similar and the only noticeable difference of the two is the better utilisations of locally generated energy and usage of the ESS by CPT2.

In order to better understand the effects of the two different targets generating strategies to the real time low level community controller and as a result to the community itself another performance metric should be introduced. The proposed performance metric needs to be able to show that by just using a constant average target instead of a dedicated higher level power profiler as the one proposed in this work can lead to a step change in demand request during the peak time period. This is due to the fact that the limitations of the low-level real time controller that are not taken into consideration by just employing an average constant power flow target. Parameters that may affect the community demand, such as the magnitude of local generation and the SOC of the ESS are obviously neglected by just using an average local target as a higher level constrain.

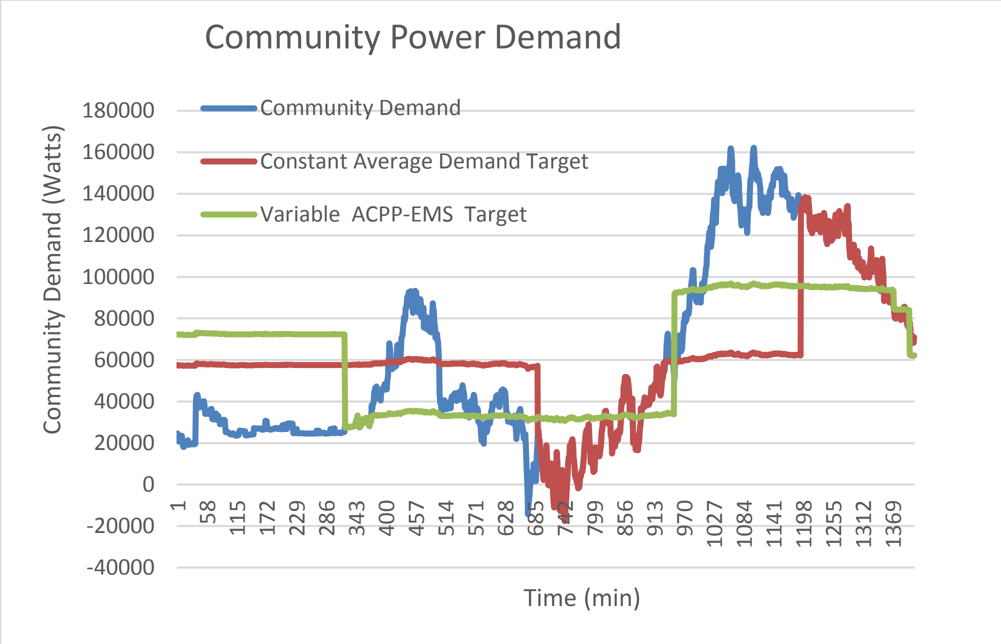


Fig 6.5 Community power demand for a summer weekday. Blue: community power demand without control. Red: community power demand with a higher level constant demand power target for the lower level real time power controller. Green: variable higher level target generated by the ACPP-EMS for the lower level real time community controller.

An example of what is described in the previous paragraph can be seen in figure 6.5. When a constant higher level target (red line), equal to the average yearly demand, is used, the low level real time controller cannot achieve the target throughout the peak time period. When the community ESS is fully charged (at about 11:30) a big trough of 50kW in the demand of power is suddenly observed. On the other hand, when the aggregated capacity of the community ESS gets depleted (at about 19:30) a huge jump in power demand from 60 to 140 kW occurs resulting in an instant change in demand request of almost 233% during peak demand period. In comparison when the higher-level target is generated by the novel ACPP-EMS controller (green line), due to the controller logic and the embedded forecast block as it is described in chapter 5 a much more predictable and smoother community power demand is achieved. The aggregated community ESS are not depleted early and the low-level real time power controller is in a position to follow the target given throughout the peak time period.

To be able to compare these strategies throughout the year, during the demand time period, the performance metric used is the average energy import during the peak demand period for every Half Hour Block (HHB) of the peak demand period time section. The average energy import for the HHB 16:00-16:30 is calculated according to (6.5). All the following HH blocks are calculated following the same logic.

$$\mathrm{AEI}_{HHB} = \frac{\left[\frac{\sum_{1}^{365} \int_{16:00}^{16:30} \mathrm{P_{imp}}}{(1000*60)}\right]}{365} \quad (6.5)$$

AEI_{HHB} is the average energy import for one half hour block and $\mathrm{P_{imp}}$ is the imported power from the grid at every step of the simulation period. By calculating the energy import for every HHB during the peak time period, large changes in power demand/energy import can be observed and assessed throughout the year as shown in Fig 6.6.

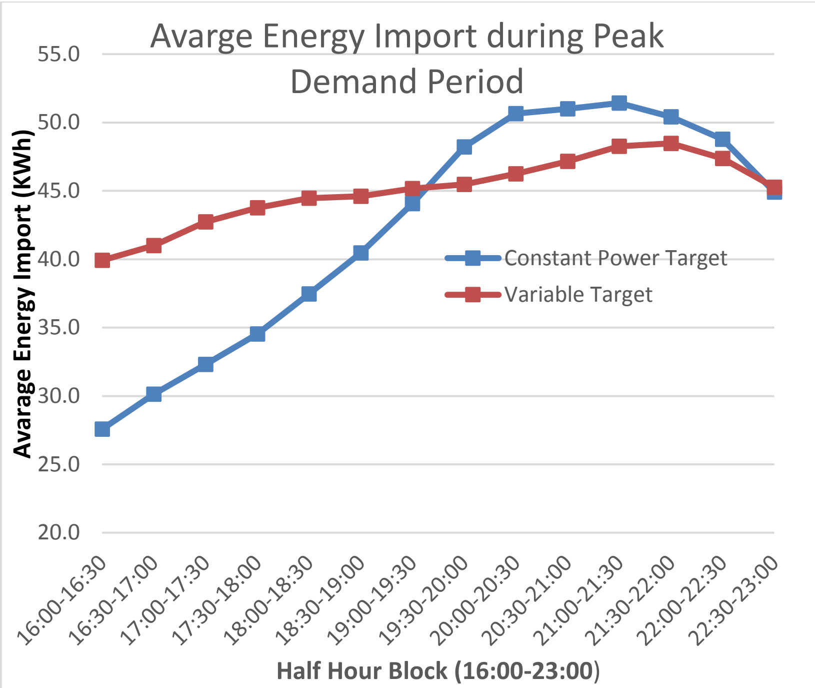


Fig 6.6 Average energy Import during peak time. Blue: Constant Higher-level target (CPT1). Red: Higher level target generated by the ACPP-EMS (CPT2).

By analysing the result presented in Figure 6.6 the average energy import throughout the year during the peak time period for the higher-level target generated by the ACPP-EMS controller (red line) is smooth and varies between 40 to 48 kWh. That shows that during the year there are no large step changes in demand during peak time period. In contrast when the constant average target is used (blue line), step demand changes are common. In Figure 6.6 the demand energy average at 16:00 hrs is 27 kWh and at 21:30 hrs reaches almost 52 kWh, a difference almost 200%.

6.2.1.3 Conclusion

It can be seen from the analysis in this section that the variable target generated by the ACPP-EMS higher level controller is superior for many of the indicators used in this comparison. Although the overall cost of import energy is similar with using a constant higher level target, the self-consumption of locally generated energy indicator, the utilisation of the capacity of the existing ESS and finally the creation of a system that is not going to create problems to the electrical grid by imposing big step changes in demand during peak demand period leads to the conclusion that even without taking full advantage of the ACPP-EMS capabilities and using it purely in power flow target generation mode, it is still advantageous for the community and the distribution electrical system that feeds the controlled area.

Tables with data for the graphs presented in this section can be found in Appendix A.

6.2.2 ACPP-EMS Controller with Frequency Regulation Services Component Enabled

The next step in demonstrating the effectiveness of the ACPP-EMS controller after introducing the power flow target generation mode in the previous section is to enable the regulation service part of the controller. The controller at this stage will also contribute to the frequency regulation market. With the regulation part also enabled, the controller while is responsible for generating power flow targets for the controlled community will also become a part of the frequency regulation mechanism. If the higher, DNO level, requires its frequency regulation services, the controller is responsible to reply with an offer of what it can achieve though the controlling area. If the offer is accepted by the DNO, then the ACPP-EMS undertakes the task to implement it through the targets that it generates for the controlled area following the control logic described in chapter 5.

For simulating the frequency regulation requests by the highest/DNO level in the proposed hierarchical structure, actual second by second electrical frequency data for the year 2015, provided from National Grid [72] to support analysis of frequency response purposes were used. The ACPP-EMS is considered a part of the post-fault secondary response service which is responsible for restoring the frequency to operational limits after breaching the 49.8 -50.2

Hz limit. Therefore, the frequency data is processed in such manner that when these limits are breached, a request is considered to be made by the DNO.

The frequency regulation market requests are made following the assumption that:

- One request can be made every 6 hours
- The agreed power target in the controlled area after an offer is accepted by the DNO should be sustained for 30 minutes.

The assumption of the 6 hour gap between requests is based on the fact that after a power target is agreed with the DNO, the dedicated part of the equivalent ESS needs to recharge (or re-discharge) after fulfilling its DNO obligation. If for instance the part of the ESS system which is dedicated to the frequency regulation market is 350 kWh (which is 100% dedicated of the ESS for the simulated community) then at any given time 175 kWh will be available for use during the half hour regulation period. This is because the dedicated part of the ESS should remain at half charge at all times waiting for a regulation request so that it can charge or discharge according to the request. When a frequency regulation request is made, for example to minimise demand, after the usage of the available 175 kWh, the ESS will need to recharge. Having a window of six hours for recharging, gives a power demand of around 29 KW. That power request is around one sixth of the community's peak power demand and it will not drastically change the community behaviour during its recharging or re-discharging period by creating unexpected peaks or troughs to the community overall power demand.

As for the requirement to sustain the agreed power demand for a duration of 30 minutes, that is a prerequisite according to National Grid [75] for frequency control by demand management.

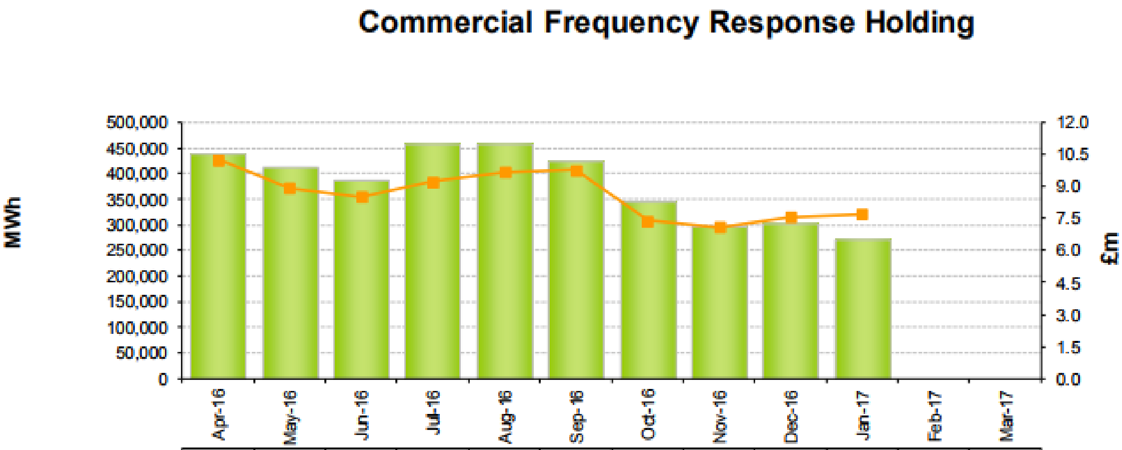
The community and the real time controller used in these simulations will be the same as the community described in section 6.3.1. The community cell used for the comparison comprises of 50 electric vehicles without any type of control. During the simulation the real time power flow controller at the lower level is responsible only for controlling the community battery with only the battery controller sub function enabled as described in chapter 4. The total installed capacity of the roof mounted PV systems is equal to 120 kWp (40% penetration) and the aggregated community BESS capacity is equal to 350 kWh.

In this section the assumption is made that there is no dedicated part of the aggregated ESS capacity of the control community for the frequency regulation market. The equivalent ESS capacity will all be used for fulfilling the community objectives. When a regulation request is made, then according to available energy and following the controlling logic described in chapter 5 an offer will be made to the DNO. A comparison between different percentages of the available ESS being dedicated for regulation purposes will then be presented in the next section.

6.2.2.1 Calculation of Frequency Regulation Services Benefit

In order to calculate the benefit gained by becoming part of the frequency regulation market a cost for providing this service to National Grid should be determined. Because contracts between participants in the scheme and National Grid are confidential, no data are available in terms of how much this service costs per kWh for each of the participants. Public available data about balancing services can only be seen in the monthly balancing service reports provided by National Grid.

From the January 2017 Monthly Balancing Service Summary [81] the commercial frequency response in terms of volume and total spent amount is shown in figure 6.7. Commercial frequency response is the terminology used by National Grid to describe services provided by generation plants through the Firm Frequency Response (FFR) and demand side management participants through Frequency Control Demand Management (FCDM). This collection of services was chosen due to its affinity with the current project in terms of providing commercial frequency response services through demand management.



	Apr-16	May-16	Jun-16	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17
Holding Volume	438,892	413,683	387,950	457,395	457,395	424,888	345,251	298,251	302,772	270,785		
Response cost	10.26	8.92	8.53	9.23	9.68	9.76	7.39	7.09	7.57	7.71		

Fig 6.7 National Grid commercial frequency response holding graph and table from Apr.2016-Jan 2017. [81]

Based on the provided data in figure 6.7 the aggregated holding volume from April 2016 to January 2017 was equal to 2743114.77 kWh and the response cost £86.14 million resulting to an average price of 31.4 p/kWh. The average price of 31.4p/kWh calculated for frequency regulation services can be considered reasonable and plausible, since is about 25% higher than the peak time price used in calculating the import energy cost obtained by the applied tariff scheme used by Green Energy UK. The proposed cost for frequency regulation services will be used in calculating the benefit for current and future scenarios.

In order to calculate the economic benefit during the simulation period, the change in demand during the half hour the regulation service is requested and used needs to be available. The benefit from the frequency regulation services is calculated according to equation 6.6.

$$B_{FRS} = \frac{\frac{\sum_{1}^{i}\left[\int_{1}^{30}\left|\mathrm{P_{dem}} - \mathrm{P_{imp}}\right|\right]}{(1000*60)} * \mathrm{P_{RS}}}{100} \quad (6.6)$$

Where P_{imp} is the import power, $\mathrm{P_{dem}}$ is the community demanded power before control, $\mathrm{P_{RS}}$ is the cost of frequency regulation calculated in the previous paragraph and B_{FRS} the benefit gain from frequency regulation services in pounds. According to (6.6) the energy used for regulation purposes is calculated through integrating, during the half hour each regulation service is used, the difference between the demanded power of the community without any control ($\mathrm{P_{dem}}$) and the actual power import (P_{imp}) and then summing all energy from the regulation periods together. In order to convert the used Power for regulation purposes in a form suitable to be proliferate with the regulation price cost (31.4 p/kWh) it should be converted in Energy (kWh), hence the division by 1000 watts and 60 minutes. Finally, to convert the calculated benefit (B_{FRS}) from pence to pounds the result goes through another division by 100 pence.

6.2.2.2 Results - Frequency Regulation Services Benefit

A comparison with the Frequency Regulation component (FRc) of the ACPP-EMS controller disabled and enabled is given in table 6.1. The comparison is carried out for a time period of one year and compares the total community's energy import cost, the energy imported during peak time period, the energy exported and ESS equivalent cycles.

1 Year							
	Cost of import Energy C_{EI} (£)	Benefit from FR B_{FRS} (£)	Total Cost C_T (£)	Energy Import During Peak time (16:00-23:00)	Energy Import (KWh)	Energy Export (KWh)	Equivalent Cycles
FRc disabled	78737	0	78737	207849	490392	4136	273
FRc Enabled	76711	1388	75322	207309	490885	4179	288

Table 6.2 Comparison of a community cell with frequency regulation component of the ACPP-EMS controller disabled and enabled respectively. 100% of ESS capacity used for local objectives.

As it can be seen in Table 6.2 the total difference in the total cost of import energy with the frequency regulation component of the ACPP-EMS controller disabled and enabled is equal to almost equal £3500. The total cost (C_T) is calculated according to (6.7) and is equal to the difference between the cost of import energy (C_{EI}) and the benefit resulting from the frequency regulation services (B_{FRS}) provided to the DNO.

$$C_T = C_{EI} - B_{FRS} \quad (6.7)$$

Although the total benefit from the frequency regulation services according to Table 6.6 is £1388 the total difference in the total cost of energy is much higher. Taking a better look at the table we can observe that the difference in the overall cost is not only the benefit gain by FR services but the actual import energy cost is lower when the FRc of the ACPP-EMS controller is enabled. While this can be considered slightly strange it can be explained by the following example.

During the peak time period of a weekday if a higher than expected frequency occurs on the grid, the DNO requests the ACPP-EMS controller to take part in the frequency regulation by absorbing more energy. During the next half hour period the target generated for the community cell to follow is very high, forcing the low level real time controller to import more power from the grid and charge the local ESS. The energy absorbed by the community cell during that half hour regulation period is not only not paid by the community but on the contrary provides a profit in the form of the frequency regulation benefit. At the same time because the ESS in the community during that half hour period is charged, due to the very high target generated, the following targets will be lower than normally planned and in that way saving more money to the community cell by lowering even further the cost of import energy.

Comparing all the other indicators of Table 6.1 it can be observed that all the energy indicators demonstrate a negligible difference as expected. The energy import during peak time period and the aggregated (total) energy import during the one year simulation period is similar since any energy that was temporarily used for regulation purposes was at a later stage reabsorbed or not demanded by the grid.

The other significant difference observed, is that the number of equivalent cycles of the ESS is higher in the case when the frequency regulation component is enabled. This is due to the rapid change of targets during the half hour regulation period that leads to using the capacity of the installed ESS more. The difference is 16 equivalent cycles for the one year simulation period which is an increase of about 5%.

Based on the given indicators, adding the frequency regulation component to the higher level controller can lower the cost of import energy an extra 26%. As stated, in this section the assumption is made that there is not a dedicated part of the aggregated ESS capacity of the control community for the frequency regulation market. A more in depth analysis about the best configuration of the ESS capacity in terms of dedicated for regulation purposes capacity of the available ESS will be presented in the next section.

6.2.2.3 Analysis of ESS Configuration

In order to gain a better understanding in the analysis of the configuration of the ESS, a more in depth understanding of the frequency regulation requests is needed. The first step is a comparison between the summer and winter period in terms of number of requests made and when they were made. The comparison is carried out between August, as a representative month for summer and November, as a representative month for winter and is presented in Figure 6.8.

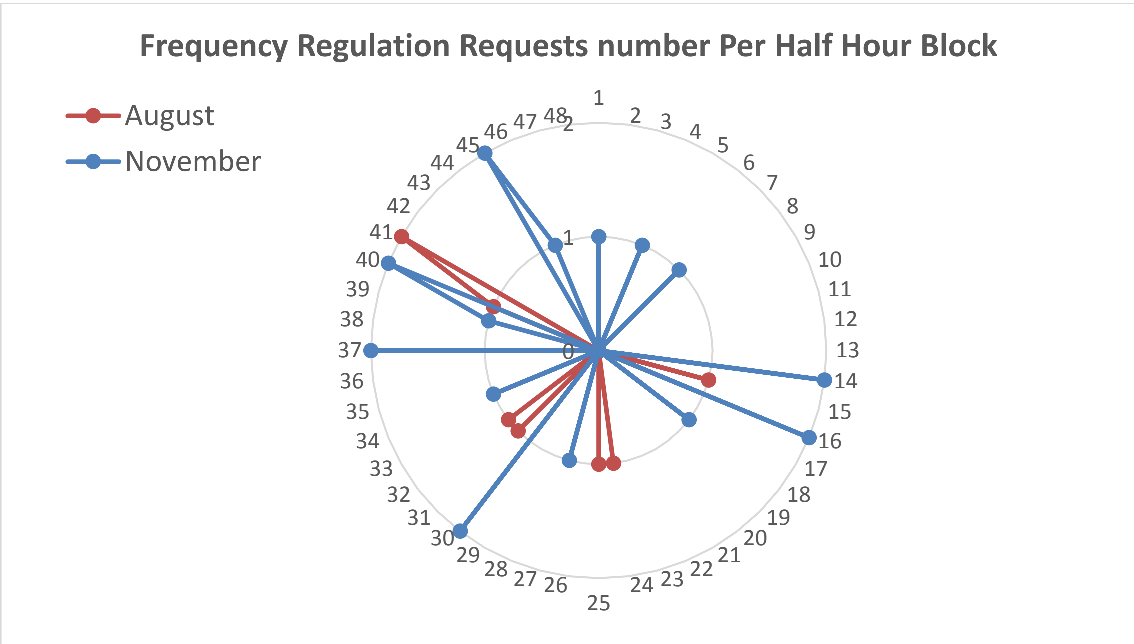


Fig 6.8 Frequency regulation requests number per half hour block for August and November months.

As it can be clearly seen in Figure 6.8, the number of frequency regulation requests required in November compared with August's frequency regulation is much higher. A logical hypothesis would be that the benefit gain from those extra November requests would be proportional to number of requests made. The cost benefit and actual number of requests is given in figure 6.9

	August	November
Cost Benefit (£)	99	142
FR. Requests Number	8	20

Table 6.2 August and November frequency requests number and benefit

The Cost benefit in Table 6.2 is calculated according to (6.6). Although according to the results presented in Table 6.2 the request made in November are 2.5 times higher than August, the benefit gain is not proportional and is only 40% higher with a difference of only £43. The explanation for this can be found returning to Figure 6.8. The frequency regulation requests in November are dispersed throughout the day. The equivalent ESS capacity is used 100% for fulfilling the community objectives and when a regulation request is made, then according to available energy an offer is made to the DNO. If a request for instance is made during the start of the peak time period to maximise the community's demand, because the ESS is almost fully charged for the coming peak time period the service it can provide is limited and so the benefit gain. Therefore the gain from the regulation requests is not proportional to the number of requests made and much lower than expected. In order to achieve the best possible results in terms of economic benefit, an analysis should be performed to determine the best configuration between the percentage of the ESS that will be used for local objectives and a dedicated percentage of the ESS only for regulation purposes.

As part of the analysis a number of simulations where performed with an incremental percentage of dedicated part of the ESS for regulations purposes and a decreasing percentage of the capacity of the available ESS to be used also for local objectives. The first simulation is with 100% of the capacity of the ESS being used both for local objectives and regulation purposes. For successive tests, the difference between the local and dedicated part of the ESS is changed by 10%. The comparison for August and November is given in Figures 6.9 and 6.10. The total cost is equal to the difference between the cost of import energy and the benefit gain from the provided regulations services and is calculated according to (6.7).

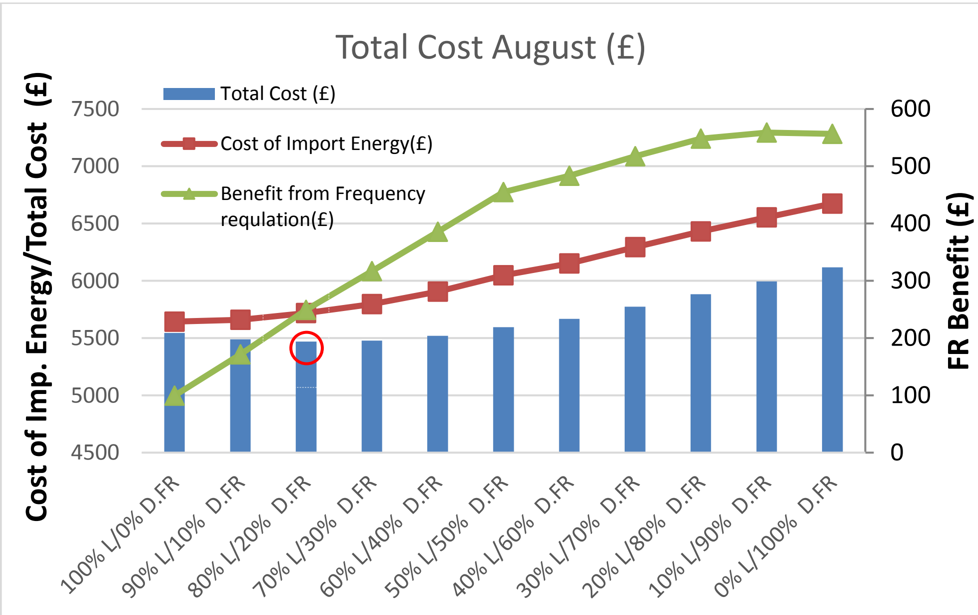


Fig 6.9 August (aggregated) total cost, cost of import energy and benefit from frequency regulation with different percentages of Local (L) and Dedicated ESS for Frequency Regulation (D.FR)

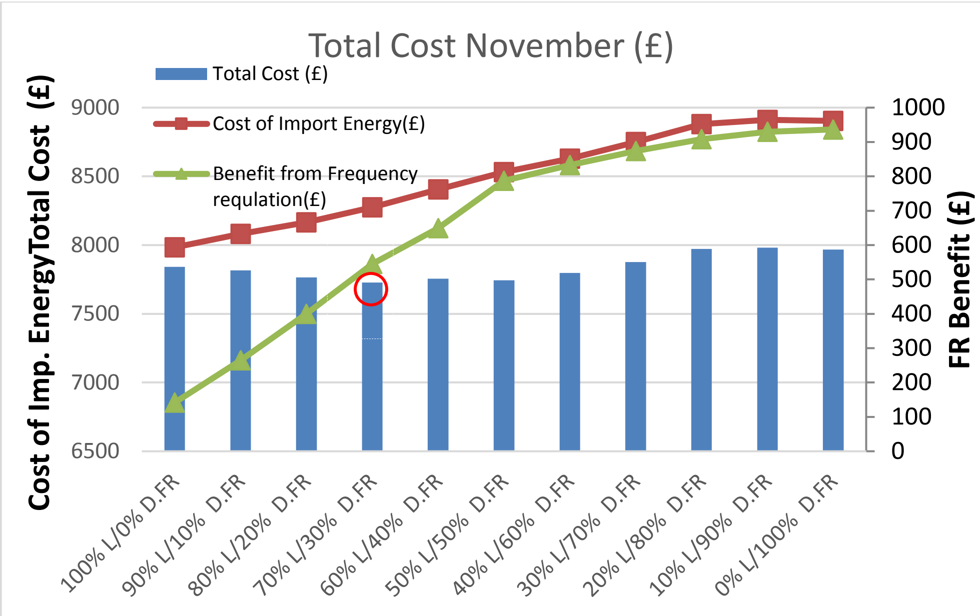


Fig 6.10 November (aggregated) total cost, cost of import energy and benefit from frequency regulation with different percentages of Local (L) and Dedicated ESS for Frequency Regulation (D.FR)

From Figure 6.9 analysing the results for August, it can be observed that the aggregated cost reduces as the dedicated percentage of the ESS increases. The best results are achieved when the dedicated FR capacity percentage is 20%. At the 80/20 configuration the aggregated cost for energy decreases to £5469. By changing the configuration of the ESS and having a part of the capacity dedicated for frequency regulation, the cost of import energy becomes higher because of the lower capacity available to fulfil the local community objectives. On the other hand the benefit gains from the frequency regulation increase as the capacity of the dedicated part of the ESS becomes larger.

The aggregate cost reduces up to the point where the benefit gains from the dedicated part overcome the losses from importing higher amounts of energy. This has to do greatly with the number of frequency requests throughout the time period compared. As was shown in Figure

6.8 and Table 6.9 the number of frequency regulation requests in November is higher than the number of frequency regulation requests in August.

Going to Figure 6.10, due to the higher number of frequency regulation requests during this time period and the much higher gains, the best configuration for the ESS capacity is different. Instead of the 80/20 configuration seen in August, the configuration with the best results for November is a 70/30, where 70% is used both for local objectives and frequency regulation and 30% of the capacity of the ESS is dedicated to frequency regulations. In the 70/30 configuration the aggregated November cost is equal to £7728, lower by £113 compared to the 100/0 configuration.

Obviously, the result presented lead to the conclusion that in order to find the most economically beneficial configuration, the same procedure should be followed for the whole year. The yearly results are given in Figure 6.11.

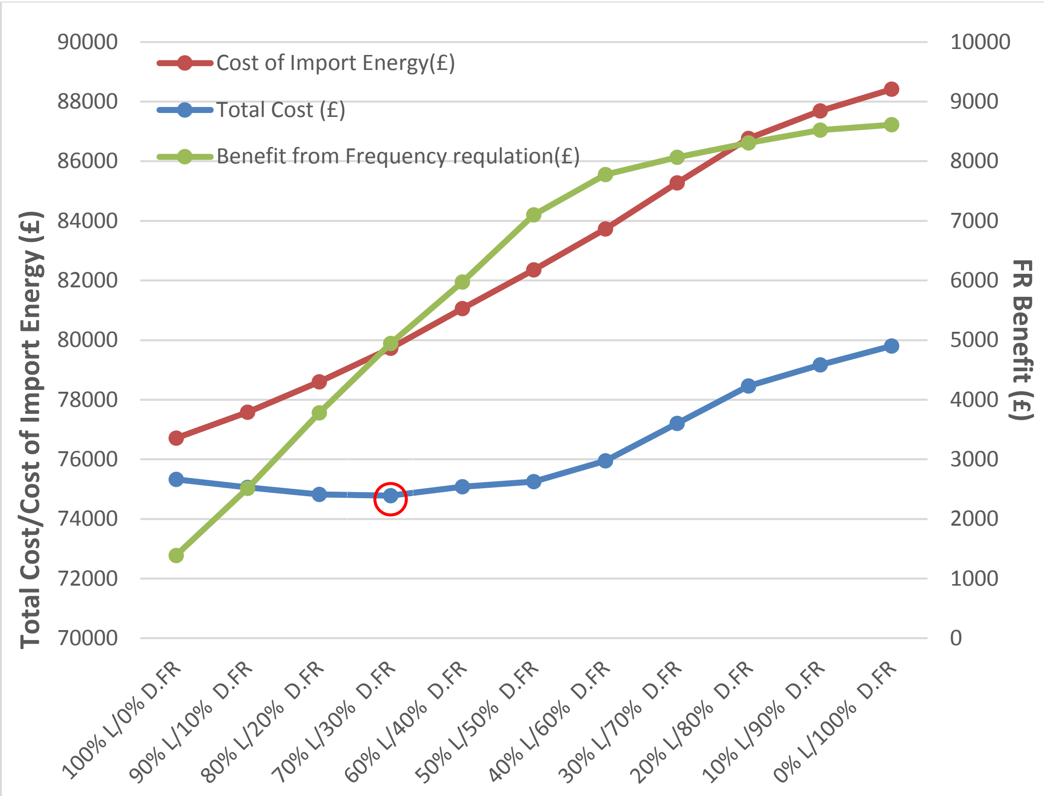


Fig 6.11 Yearly (aggregated) total cost, cost of import energy and benefit from frequency regulation with different percentages of Local (L) and Dedicated ESS for Frequency Regulation (D.FR)

According to Figure 6.11 the best configuration for the simulated community is a 70/30 configuration marked with a red circle. By having a 30% dedicated part of the ESS for frequency regulation, the total benefit can be increased even further by 15% (almost £550) for the whole year when compared to a 100/0 configuration. The cost of import energy at the 70/30 configuration is increased by £3013 but at the same time the benefit from the dedicated part of the ESS is equal to £3553. After that configuration point the increase in the benefit gain cannot cover the increase of the cost of import energy leading to a higher aggregated overall cost of energy.

Another parameter that needs to be emphasised, is the fact that the presented results in the previous paragraphs are price sensitive. By increasing or decreasing the cost price of the regulation services, the optimum configuration of the ESS in order to acquire the maximum possible benefit changes. An example of how a change in the price affects the optimum configuration is given in Figure 6.12.

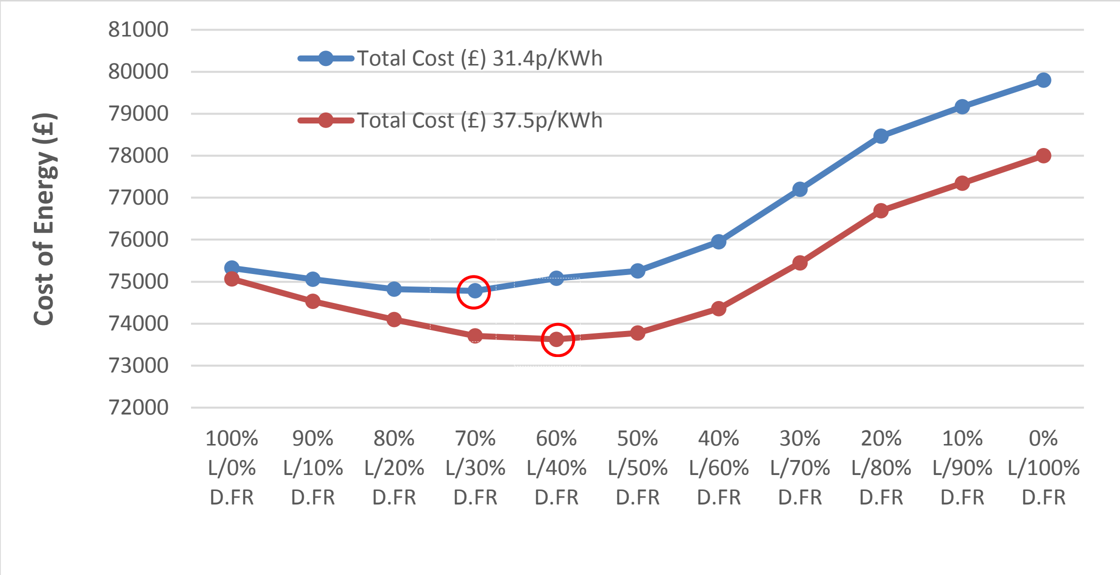


Fig 6.12 Yearly (aggregated) total cost with different percentages of Local (L) and Dedicated ESS for Frequency Regulation (D.FR) for different prices of frequency regulation cost.

The two frequency regulation cost prices chosen to demonstrate the price sensitivity of the optimum configuration of the ESS that are compared in Fig. 6.12 are 31.4 p/KWh (calculated in section 6.3.2.1 - 25% higher than peak time tariff) and a price of 37.5p/KWh which is 50% higher of the peak time demand tariff.

In Figure 6.12 the best configuration for each price in terms of minimum aggregated total cost is marked with a red circle. The results are for a time period of a year. As seen in the previous paragraph with a price of 31p/KWh the best yearly configuration is 70/30 and a total cost of £74782. By changing the regulation service price to 37.5p/KWh the optimum configuration becomes 60/40 with the dedicated capacity of the ESS becoming 40% and the total/aggregated cost of £73628. As expected by having a higher frequency regulation price, increases the benefit gain from the dedicated capacity of the ESS for frequency regulation and in this way favouring higher dedicated configurations.

In addition to the sensitivity price analysis for the optimum ESS configuration, the optimum energy storage configuration is also sensitive to the number of frequency regulation requests. This is important since a logical hypothesis about the future electrical system is that as the penetration of intermittent renewable forms of generation becomes larger the system will become weaker, hence the DNO of a weaker electrical system will ask for frequency regulation services more frequently.

The frequency regulation request scenarios chosen to demonstrate the sensitivity of the optimum configuration of the ESS toward the FRR number are:

a) the stated at the start of this chapter based on the actual electrical frequency data for the year 2015, provided from National Grid [72] and

b) a second scenario with 10% higher number of FRR. The two scenarios are presented in Fig. 6.13.

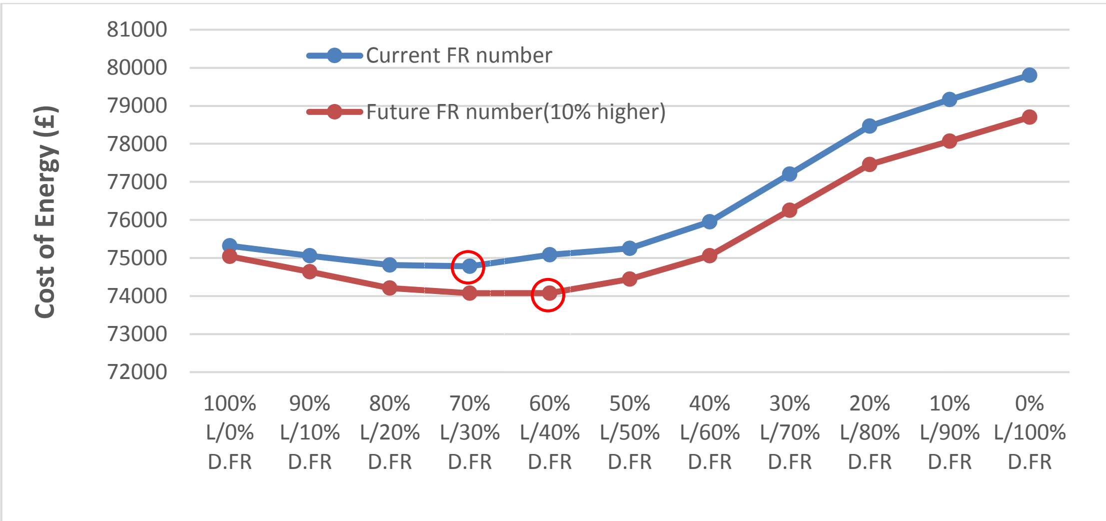


Fig 6.13 Yearly (aggregated) total cost with different percentages of Local (L) and Dedicated ESS for Frequency Regulation (D.FR) for a different number of frequency regulation requests.

In order to add the extra 10% of FRR for the second scenario in a statically correct method the number and type of each request was analysed per month. The FR requests were distinguished into request to maximise or minimise demand respectively and their number for each month was calculated. From the acquired results the total number of FR requests to maximise demand was 141 for a year and the request to minimise demand 53. Furthermore, based on the results for each month the probability of encounter a FRR per type of request per month was calculated and is presented in Table 6.3

Frequency Requlation Requests Probability of Ecounter and Type per Month		
Month	FR -Maximise Demand (%)	FR- Minimise Demand (%)
Jan	0.14	0.21
Feb	0.12	0.15
Mar	0.09	0.08
Apr	0.04	0.08
May	0.06	0.02
Jun	0.02	0.02
July	0.05	0.02
Aug	0.06	0.04
Sept	0.07	0.08
Oct	0.11	0.13
Nov	0.11	0.09
Dec	0.13	0.09

Table 6.3 Frequency Regulation Request probability and type per month

According to the probability that each FRR type is encounter the extra 10% of frequency regulation requests over the whole year were added to the existing request file. For instance the FRR requests to maximize the demand yearly number is 141. Adding an extra 10% requires to add 14 more FRR of the same type. In order to add them at each month the number of extra FRR is multiplied by the probability to encounter the type per month, in January 2 extra FRR to maximise demand were added since 14 X 0.14 ≈ 2.

Based on the result for each scenario in Figure 6.13 the best configuration in terms of minimum aggregated total cost is marked with a red circle. The results are for a time period of a year. As it can be observed with the existing FRR number the best yearly configuration is 70/30 and a total cost of £74782. By increasing the number of FRR by 10% the optimum configuration becomes 60/40 with the dedicated capacity of the ESS becoming 40% and the total/aggregated cost of £74077. As expected by increasing the number of frequency regulation requests throughout the year, the cost benefit is increased by having a larger dedicated ESS capacity for frequency regulation.

Tables with data for the graphs presented in this section can be found in Appendix B.

6.2.3 Energy Storage System - Economic Analysis

In order to analyse the payback period for ESS capacity installed in the community, new investment indicators should be introduced. The first and simplest one is the Simple Payback Period (SPP) and it is presented in (6.8).

$$SPP = \frac{C_o}{C_i} \quad (6.8)$$

Where C_o is the cash outflow/project cost and C_i the cash inflow/profit from the project. Although this simple calculation can give a quick and simple indication when comparing different projects, it does not take into account how the lucrativeness of long term projects changes over time. In order to get more realistic and trustworthy results another indicator needs to be introduced.

One of the most common and important tools used to evaluate long terms projects is the Net Present Value (NPV) indicator. The tool is used to check in how many years the cost of a project would be recovered and by what time period it will start providing benefit for the investors. The major benefit of using the NPV tool is the use of an interest rate. The interest rate value is used to determine the present value of future cash flows. This means that both the time value of money but also the risk of uncertainty for future cash inflows can be accounted for. The NPV indicator is calculate according to (6.9).

$$NPV = \sum_{t=1}^{n} \left[\frac{C_t}{(1+r)^t}\right] - C_o \quad (6.9)$$

Where C_o is the cash outflow/project cost and C_t is the he cash inflow per year, r is the interest rate and t is the time in years.

The interest rate does not remain constant but changes to determine the changing value of money. For long term projects in order to determine an appropriate interest rate many companies use what is known as their Weighted Average Cost of Capital (WACC). The WACC can be described as a company's cost of capital and the weighted value that includes that company's equity, debt and the percentage of financing. Since the WACC used as an interest rate is unique for each company and based on its individual financial data, an appropriate value cannot be calculated for this project. Instead, based on a KPMG report for the cost of capital [82] an average WACC for the energy and natural resources industry was used. The average WACC according to the report for 2015 was equal to 6.1%.

Furthermore, in order to be able to calculate the NPV, the project cost needs to be known. To calculate the appropriate cost of the aggregated ESS installed in the simulated community, the information available from the TESLA powerwall Battery ESS were used. According to the technical specifications of the system [9] a 14 kWh powerwall battery and supporting equipment including VAT costs £5900. In addition the manufacturer in the specifications manual claims a 100% depth of discharge resulting in a capital cost of £421.43 per kWh of installed capacity. With the aggregated installed capacity in the simulated community equal to 350 kWh the capital cost C_o is therefore approximately £147500. In the cost calculation the PC equipment running the controller algorithms and communication equipment cost is neglected as it is considered small compared the BESS capital cost and it does not affect the overall comparison results since it is identical in all the following compared scenarios.

Finally for the calculation of the annual cash inflow (C_t) for each of the compared cases the difference between the cost of import energy of the community cell without any type of control with the cost after the implemented control schemes was used. The cash inflow for each of the compared cases is given in Table 6.4

Yearly		
	Cost of Import Energy (£)	Cash Inflow(Ct) - (£)
No Control	91996.37	-
ACPP-EMS/Disabled FR.	78737	13260
ACPP-EMS /Enabled FR	75322	16674
ACPP-EMS /Enabled FR 70/30%	74782	17215

Table 6.4 Yearly Cost of Import Energy and Cash Inflow

The compared cases are the three scenarios presented in the previous sections. The first case is the one presented in section 6.3.1, where the ACPP-EMS higher level controller generates a variable target for the lower real time controller to fulfil the local community objectives. In this case the Frequency regulation service part of the controller is disabled. The second case is presented in section 6.3.2.1 with the frequency regulation service part of the ACPP-EMS controller enabled and 100% of the available capacity used for both local and global benefit and the final and third case is presented in section 6.3.2.2, with the optimum configuration of the capacity of the available ESS to maximise the benefit from the frequency regulation service. In the calculations the yearly cash inflow is considered constant for all the years. The results of SPP and NPV are presented in figures 6.14 and 6.15.

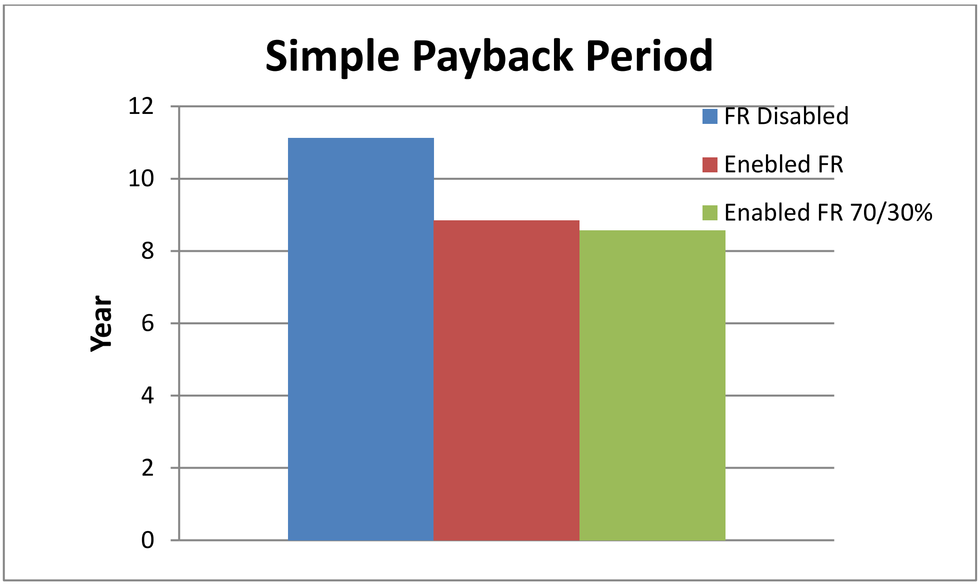


Fig 6.14 Simple Payback Period comparison.

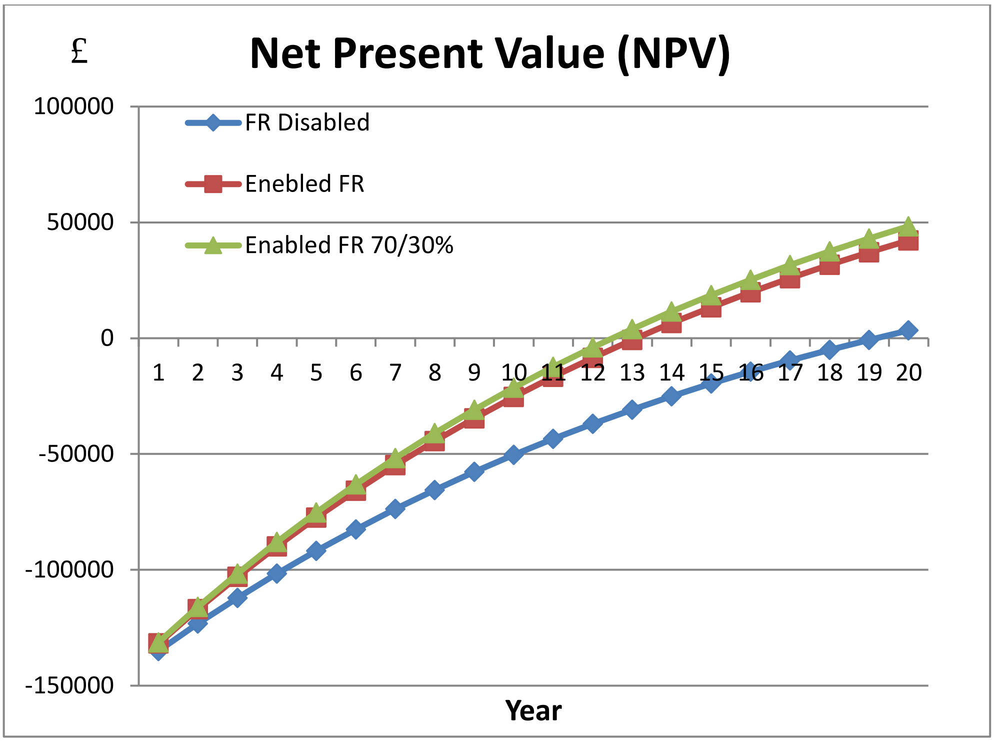


Fig 6.15 Net Present Value (NPV) comparison.

According to Figure 6.14 the simple payback period of the system is 11 years with the frequency regulation part of the controller disabled, almost 9 years with the FR service enabled and 8.5 years with the system configuration optimised. Although the above results show clearly that by becoming a part of the frequency regulation market can highly facilitate and benefit the implementation and usage of ESS in communities, is simplistic and do not give a realistic evaluation of the time frame required to repay the investment but can only be used to compare investment and get a rough idea for the most beneficial.

A more realistic evaluation about the time frame required to repay the BESS is given in Figure 6.15 with the NPV indicator. When the result is negative the investment has not been paid back yet and more years are required. When the NPV value becomes positive the payback period has finished and the savings count as the investments profit. As explained previously due to the interest rate used in the calculation of the NPV value the furthest the cash inflow is into the future, the lower its present value is.

It can be observed that the repayment of the ESS when the frequency regulation service is disabled requires twenty years, nine more than when compared to the simple payback period. Obviously according to the NPV indicator the twenty year payback period is long and as presented in chapter 2 equal to the considered calendar lifetime of ESS in [17, 18, 19]. Hence the investment is not desirable.

On the other hand, with the frequency regulation part of the ACPP-EMS controller enabled, the payback period of the ESS is thirteen and twelve years respectively, showing a beneficial investment that can create enough revenue for its investors. Due to the fact that the analysis was based on the cost of the Tesla Powerwall BESS. The maintenance cost and battery degradation costs are neglected since according to the Tesla Powerwall information sheet [9] no maintenance is required and the system has a warranty for 10 years.

Tables with full data for the graphs presented in this section can be found in Appendix C.

6.2.4 Lower Level Real Time Controller Impact –Controlled and Uncontrolled charging of EVs.

As described in Chapter 4 the low-level community real time controller is divided into two main control sub functions. The EV charging control function responsible for controlling the charging of the EVs inside the controlled community cell and the community battery control function responsible for the community's ESS by following the higher-level hierarchical target.

Up to this point of the analysis, the results in the previous sections of the chapter were presented with the lower level EV charging control sub function of the community real time controller disabled. The reasoning was based on the assumption that if good result can be achieved with such a simple low level controller, a more sophisticated real time controller with Demand Side Management capabilities for important community level loads can improve the results even further.

In order to check if the previous assumption is valid, the EV charging control sub function of the low-level real time controller needs to be enabled and a comparison should be carried out between the results acquired up to this point and the result with the lower level controller having some DSM capabilities.

When the EV charging control sub function of the real time controller is enabled, it does not allow the charging of EVs and delays the start until the end of the peak time period. After and before the peak time, the EVs can charge without any control. If an EV starts charging before entering the peak time period, the charging procedure will not be disturbed and will continue until fully charged.

The reasoning behind the EVs charging control being limited during the peak demand period is based on the fact that the highest percentage of EV charging requests occurs during the initial hours of the peak demand period. As explained in section 4.2 this is due to the fact that according to the statistical analysis results of car usage, peak demand period is also the time that a very large proportion of the population use their vehicles to return home after work.

6.2.4.1 Controlled and Uncontrolled EV charging and Impact

The comparison between the two different scenarios will be made in terms of cost. The higher level ACPP-EMS controller will be the same for both scenarios according to the best achieved results as presented in section 6.3. The ESS capacity configuration will be 70/30, with 30% being dedicated for frequency regulation. The difference between the two scenarios is in the lower/real time controller. In the first case the EV charging control sub function is disabled and in the second scenario the sub function is enabled. The results are presented in Table 6.5.

Year					
	Cost of Import Energy(£)		Benefit from Frequency regulation(£)		Total Cost (£)
ACPP-EMS /Enabled FR 70/30%-No EV control	79723		4942		74782
ACPP-EMS /Enabled FR 70/30%- EV control	73123		5048		68076

Table 6.5 Yearly Cost with the EV charging sub function at the lower/real time controller enabled and disabled.

According to Table 6.5 when the EV charging control sub-function is enabled, the total (aggregated) cost for a simulation period for one year is lower by £6700 in absolute numbers or 9% when compared to the cost of the first scenario. The results are as expected since 99% of the cost difference are due to the saving from the cost of import energy. The cost of import energy is much lower when EVs are prohibited from charging during the peak tariff period. Each EV charged by a domestic electric socket is a demand load equal to 3 kW. In a small community with a high penetration of EV, the aggregated demand from the charging EVs can highly impact the overall community demand as can be observed in Figure 6.16.

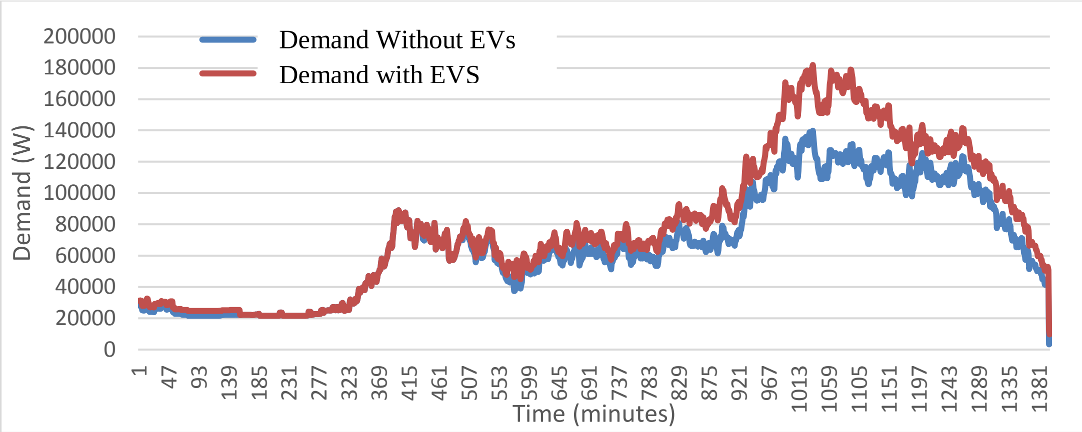


Fig. 6.16 Comparison of a community's one day demand profile with and without EVs. The community consists 100 dwellings and 50 Electric Vehicles

In Figure 6.16 it can observed that by removing the EVs from the community cell, the demand profile during the peak tariff period is significantly altered. In the same manner by controlling the EVs charging during the peak tariff period can significantly lower the cost of import energy.

The benefit from frequency regulation is very similar in both cases and the difference is negligible over the period of one year. Due to the fact that the higher level ACPP-EMS controller adapts to the new demand profile and uses the available community energy resources in the best possible manner according to its control logic as presented in Chapter 5 the benefit from frequency regulation remains similar.

A further hypothesis based on the presented results up to this point can be made that by enabling the EV charging control sub-function on the lower level real time community controller (DSM capabilities), similar results in term of energy import during peak demand/peak tariff period, as the results presented in section 6.2 (real time low level controller without DSM capabilities), can be achieved by having lower capacity energy storage systems. Since during peak demand period and peak tariff period coincide, either of the magnitude of energy import during the specified time period or cost of import energy can be used to check the above hypothesis. In this section the energy import volume will be used.

For comparison purposes the volume of energy imported during the peak demand period of the community without any control and the energy imported with only the lower level EV charging control enabled are also presented. In order to size the benefit of having DSM capabilities (EV control) at the lower cell level controller the energy import volume with:

a) the higher level ACPP-EMS enabled and no EV charging control at the lower level real time controller and

b) with both the ACPP-EMS and the lower real time EV charging controlling enabled

is presented in Figure 6.17. The results are given for a time period of one year.

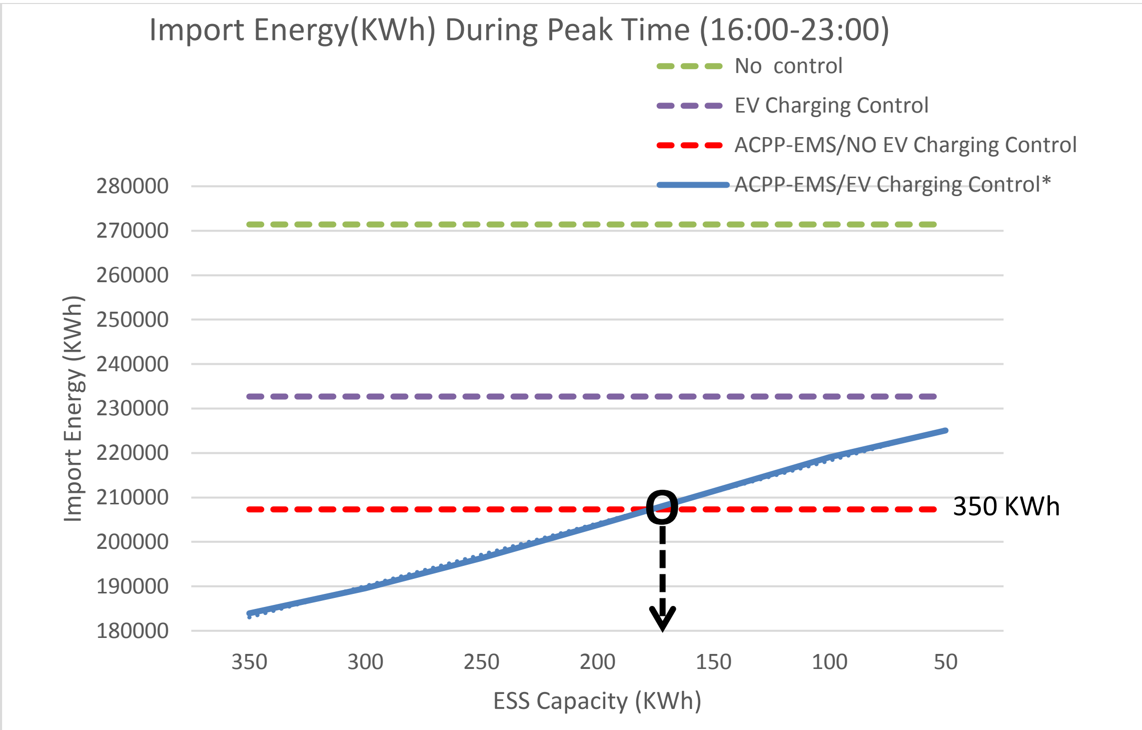


Fig. 6.17 Yearly Energy Import for a community without any control, with EV charging control (low level-real time controller), with ACPP-EMS enabled and no EV charging control at the low community level and with ACPP-EMS enabled and EV charging control. The community consists 100 dwellings and 50 Electric Vehicles

The import energy of the community without any control and with just the lower level real time controller EV charging control enable are given for comparison purposes. For these two scenarios the ESS in the community is not used and is not taken into account. The EV charging controller as described above is a sub function of the low-level real time controller that does not allow the charging of EVs and delays the start until the end of the peak time period. In all cases ACPP-EMS controller is fully enabled

At the lower community cell level when the real time power flow controller has only the battery controller sub function enabled as it can be observed in Fig. 6.17 the yearly energy import is equal to 207309 kWh (red line). The community has an aggregated equivalent capacity ESS equal to 350 kWh as used during the whole chapter.

In order to quantify the difference with lower level rear time controller having DSM capabilities, the EV charging controller sub function of the real time controller is enabled. A number of simulation iterations are executed with different size BESS starting from 350 kWh and decreasing the capacity of the system in 50 kWh steps while at each step the energy import is measured. The results are given in Fig. 6.17, blue line. X is the axis of the BESS capacities used during the simulation runs (350 kWh-50kWh).

While the ESS capacity becomes smaller the energy import during peak demand period becomes higher and at the point where the two lines (red and blue) intersect the energy import is identical. This point is marked with a black circle on Fig. 6.17. At that point the capacity of the ESS (blue line) when seen on the x axis is almost equal to 175 kWh. The results is 50% smaller than the scenario without any lower level EV shifting capabilities (red line).

The above analysis demonstrates our previously formulated hypothesis and lead's to the conclusion that with a more sophisticated lower level controller working together with the higher level proposed ACPP-EMS, similar results can be achieved with smaller capacity of ESS or the same ESS can achieve even better results.

Tables with full data for the graphs presented in this section can be found in Appendix D.

6.2.4.2 Impact of Number of EVs as part of the community cell load

Up to this point in all the scenarios preceded the EV penetration is considered to be 50%. The 50% penetration is considered to be a highly realistic future community load scenario as according to the near future plugged EVs sales estimations will account to a large portion of the total number of automobiles sold. According to Hadley et al [16] by 2020 almost 25% of all the automobiles sales will be PEVs.

Although the used community cell is realistic as a future scenario, a more current or near future community cell includes a much lower EVs penetration level. In order to examine the impact of a lower number of EVs at the community cell, a comparison between the two different scenarios will be made. The higher level ACPP-EMS controller will be the same for both scenarios according to the best achieved results as presented in section 6.3. The ESS capacity configuration will be 70/30, with 30% being dedicated for frequency regulation. The difference between the two scenarios is at the community cell load demand profile. In the first case the EVs penetration level is 50% (50 EVs) and in the second scenario the penetration level will be half, equal to 25% (25EVs). The results are presented in Table 6.6.

Year							
	Cost of Import Energy(£)		Benefit from Frequency regulation(£)		Total Cost (£)		Peak Time Energy Import (KWh)
50% EVs penetration	79723		4942		74782		207849
25% EVs penetration	73123		5048		68076		193871

Table 6.6 Yearly Cost with the 50EVs and 25 EVs at the community cell.

According to the presented results in Table 6.6 the difference in the total cost of the imported energy for a community cell with 25 EVS is lower by around £8000 in absolute numbers. Although the big difference in total cost, the benefit gain from frequency regulation is similar in both scenarios and 99% of the cost difference is due to importing less energy to serve the existing load. This can be confirmed through comparing the energy import during the peak demand time period. The difference of energy import during the peak time period is almost 14000 KWh for the year.

The results are as expected in terms of frequency regulation benefit. The ACPP-EMS controller due to its controlling logic and usage of demand prediction adjusts to the different demand consumption. The generated power targets for the lower community real time controller intent to take full advantage of the existing lower level energy storage capabilities to fulfil local objectives therefore in both scenarios the capacity used for frequency regulation is similar, hence the regulation benefit is also identical.

In conclusion the difference in total cost is due to the lower community demand, especially during peak time period, due to fewer EVs and the opportunity given to the ACPP-EMS controller to minimise the peak energy demand even further through energy shifting.

6.3 Energy Storage System Sizing Methodology Validation

The Sizing methodology as presented in Chapter 4 is based on confidence levels. A confidence level of target achievability is the likelihood of the community achieving the predetermined power target using the energy storage system available. The probability of the community cell to meet the target through the available ESS can be expressed as:

$$S_i = \begin{cases} 1: P_i \le P_{rated} \ \& \ SOC_l < SOC_i < SOC_h \\ 0: P_i > P_{rated} \ \text{or} \ SOC_i \le SOC_l \ \text{or} \ SOC_i \ge SOC_h \end{cases}$$

Where S_i represents the state of success of achieving the power target at the *i*th time period, P_i is the power request from the available ESS at the *i*th time period, SOC_i is the State Of Charge of the ESS at the at the *i*th time period, SOC_l is the lower limit of state of charge and SOC_h the higher limit of state of charge. Then the confidence level of achieving the power target is given by (6.10)

$$P_{cta} = \sum_{i=1}^{N} \frac{S_i}{N} \qquad (6.10)$$

where N is the total number of samples.

During the sizing of ESS of the "community cell" used throughout the results chapter, the higher hierarchical level target used for the calculation was a constant target equal to the net yearly average power demand as a more generic target. In order to validate the proposed methodology, the optimum power and capacity rating for the 90% confidence level as resulted by the proposed methodology is tested with variable targets generated by the novel higher level ACPP-EMS controller and followed by the lower "community cell" (Proposed Hierarchical Control). The confidence level results for the validation simulation were calculated using (6.10) and are presented in Table 6.6

	90% Confidence
	95 KW, 600KWh
Month	V. Simulation Confidence
Jan	0.89
Feb	0.91
Mar	0.92
Apr	0.94
May	0.94
Jun	0.93
Jul	0.93
Aug	0.96
Sep	0.94
Oct	0.94
Nov	0.91
Dec	0.92
Year	0.93

Table 6.6 Results of confidence interval simulated using the proposed hierarchical framework for ESS sizing methodology optimum results for 90 % confidence levels

As it can be observed in Table 6.6 for each of the 90% confidence level used during the ESS sizing procedure, the optimum result was tested using the higher level ACPP-EMS for the generation of the "community cell" profiling targets to be followed. The confidence level of the validation simulation was calculated for each month and for the whole year of the simulation period. In each confidence level the results for each month are very near the expected confidence and as a result the yearly confidence level is also near the expected level.

The yearly results are slightly higher than the estimated confidence levels during the sizing methodology, due to the fact that the sizing procedure was made following a constant target equal to the net yearly average power demand.

Chapter 7: Conclusions

7.1 Proposed Hierarchical Control Structure and Models Developed

The aim of this project, as stated in Chapter 1, was to investigate how domestic ESS can contribute to FR and at the same time provide benefit for electricity end users through achieving local community objectives. This aim originated from a number of hypotheses that needed to be addressed. New small scale residential BESS (Tesla Powerwall) tend to have a higher capacity than already existing energy storage system. Can this higher capacity provide benefit for both the electricity end users/owners of the system and DNOs through frequency regulation? Can this benefit be maximised through an energy community entity?

In the process of tackling these questions a novel control framework able to exploit community ESS, for both local and community benefit through energy import cost reduction and at the same time able to provide to the grid operator frequency regulation ancillary services was proposed. The proposed hierarchical frameworks consists of three distinct parts with each one having different responsibilities and roles within the overall framework structure:

- The low-level real time community controller, responsible for the real time power balancing by regulating the community's active power import by following a power reference target
- The higher-level community profiler (ACPP-EMS), which acts as an intermediate between the lowest and the highest framework level and is responsible for generating the power reference targets for the lower community controllers according to the energy management objectives

- The highest level the, Distributed Network Operator (DNO), responsible for the overall operational health of the entire electrical grid and as part of the proposed framework in charge of the task to communicate with the community profiler through frequency regulation requests.

In order to simulate the proposed control framework and address the stated issues a number of models were required to be developed or implemented from the available literature.

Starting from the lower level "community cell" a residential electricity demand model and battery energy storage system (BESS) was adopted from existing models. In addition, a novel electric vehicle model (EV) was developed and a lower level real time power flow controller was introduced. Finally, real data from photovoltaic system and the electrical system frequency data were analysed and used as part of the simulation procedure.

The novel higher-level community profiler, Adaptive Community Power Profiler –Energy Management System is the control algorithm developed that is able to provide local and national benefit through the exploitation of small scale community ESS. The ACPP-EMS is the major contribution of this project.

In order for the ACPP-EMS to be constructed the control algorithm was divided into different control entities according the energy managements objectives it is required to achieve and as it can be seen in Figure 7.1.

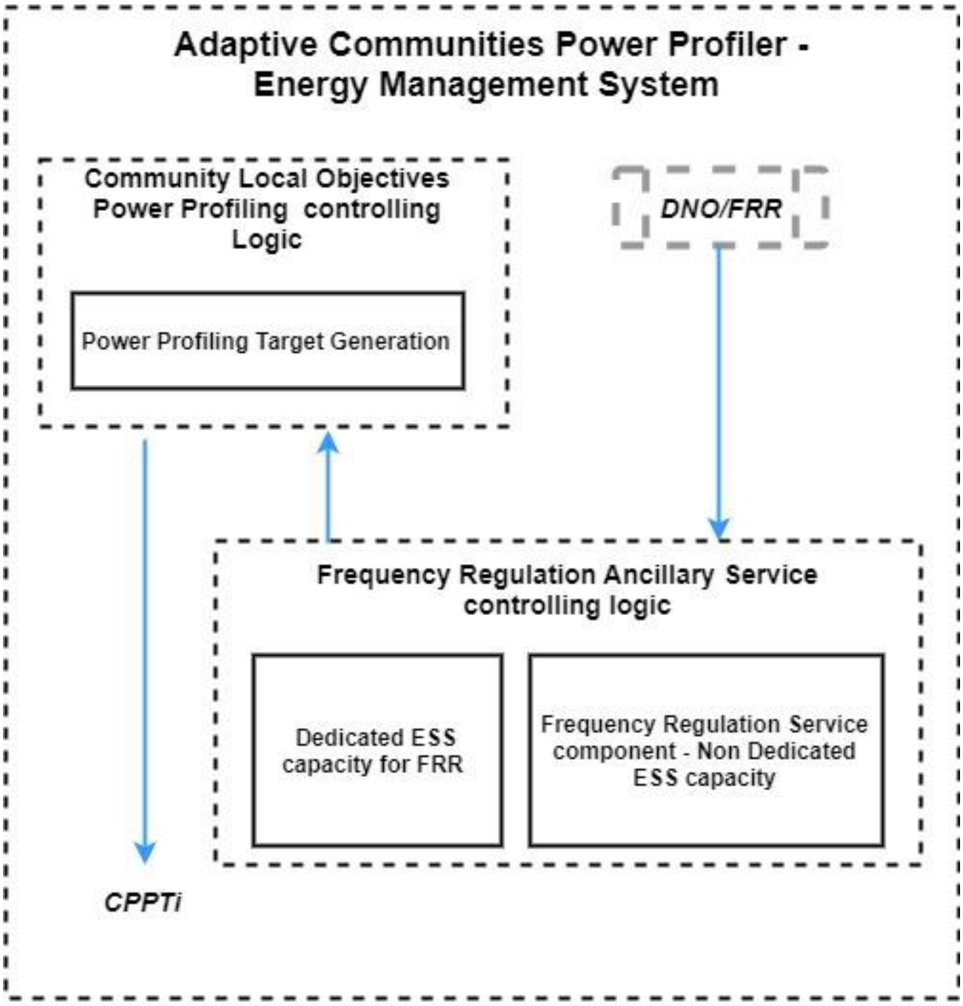


Fig. 7.1 ACPP-EMS controller main controlling logic blocks

The Community Local Objectives Power Profiling Controlling Logic entity, responsible for configuring the power profile of the controlling "community cells" by imposing the generated profiling power targets for the day ahead in order to achieve its main local/community objectives. The most important of these objectives are the maximisation of self-consumption of locally generated renewable energy and the minimisation of energy import during peak demand periods together with associated economic benefit.

The Frequency Regulation Ancillary Service logic block entity responsible to provide the best possible result within the communities' capabilities when the DNO communicates and a frequency regulation request is made. As it can be observed the Frequency Regulation Ancillary Service logic block is divided further into two sub logic entities. One is responsible for the part of the ESS that is dedicated to frequency regulation and the other exploits the available capabilities of the "community cell" for frequency regulation in when an FRR is made.

The Highest DNO level of the hierarchical control framework was simulated through frequency regulation requests based on real second by second electrical frequency data for the year 2015, provided from National Grid.

In addition, as part of the project a novel Energy Storage System sizing methodology for calculating the required battery size (aggregated) to achieve the aforementioned objectives was developed based on chosen confidence levels.

7.2 Simulation Results and Analysis

Based on the proposed control framework and the models developed, the stated original hypotheses were tested and the results analysed. To demonstrate the effectiveness of the ACPP-EMS and test the hypothesis that benefit for both the electricity end users/owners of the system and DNOs through frequency regulation can be achieved, the proposed control framework was simulated for a year with the ACPP-EMS controller having the Frequency Regulation Ancillary Service component firstly disabled and afterwards time enabled. The results are presented in Table 7.1.

1 Year			
	Cost of import Energy C_{EI} (£)	Benefit from FR B_{FRS} (£)	Total Cost C_T (£)
FRc disabled	78737	0	78737
FRc Enabled	76711	1388	75322

Table 7.1 Comparison of a community cell with Frequency Regulation Ancillary Service component of the ACPP-EMS controller disabled and enabled respectively. 100% of ESS capacity used for local objectives

As it can be seen in Table 7.1 the difference in the total cost of import energy with the frequency regulation component of the ACPP-EMS controller disabled and enabled is equal to almost equal £3500 and the benefit just from providing FR services £1388. It needs to be emphasized that in the presented results 100 of the "community cell" aggregated ESS capacity was used for both local objectives and FR purposes.

The optimum ESS capacity configuration in terms of dedicated and non-dedicated capacity to be used by the ACPP-EMS controller as part of the frequency regulation ancillary service or for both local and global (FRR) objectives were also researched and the results are presented in Figure 7.2

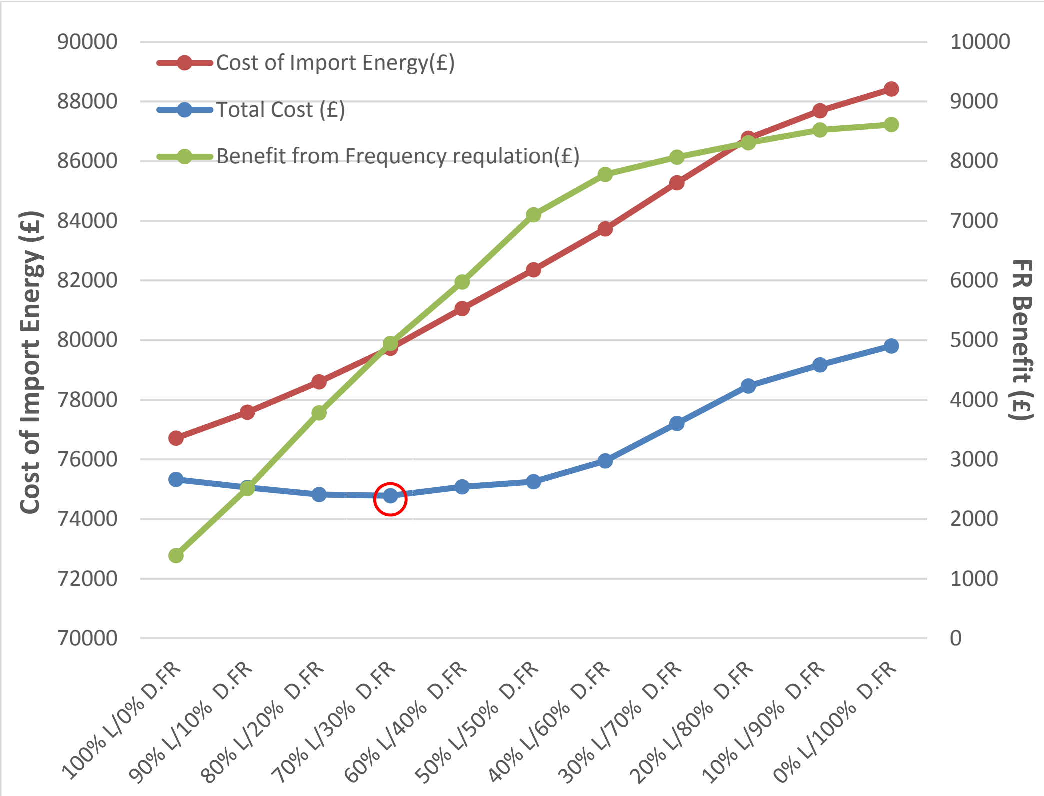


Fig 7.2 Yearly (aggregated) total cost, cost of import energy and benefit from frequency regulation with different percentages of Local (L) and Dedicated ESS for Frequency Regulation (Global)

As it can be seen in Figure 7.2 the best configuration for the simulated community is a 70/30 configuration noted with a red circle. By having a 30% dedicated part of the ESS for frequency regulation the benefit can be increased even further by 15% (almost £550) for the whole year when compared to a 100/0 configuration. The cost of import energy at the 70/30 configuration is increased by £3013 in order to provide the required community cell energy demand but at the same time the benefit from the dedicated part of the ESS is equal to £3553.

The most common tool to evaluate long term projects in term of economic benefit is the Net Present Value indicator. The tool provides an estimation in how many years the cost of a project will be recovered and the investment will start providing benefit. In Figure 7.3 two scenarios are presented. The scenario with the ACPP-EMS controller generating targets for the lower real time controller to fulfil local community objectives and the scenario with the Frequency Regulation Ancillary Service controlling logic enable and the system part of the frequency regulation market.

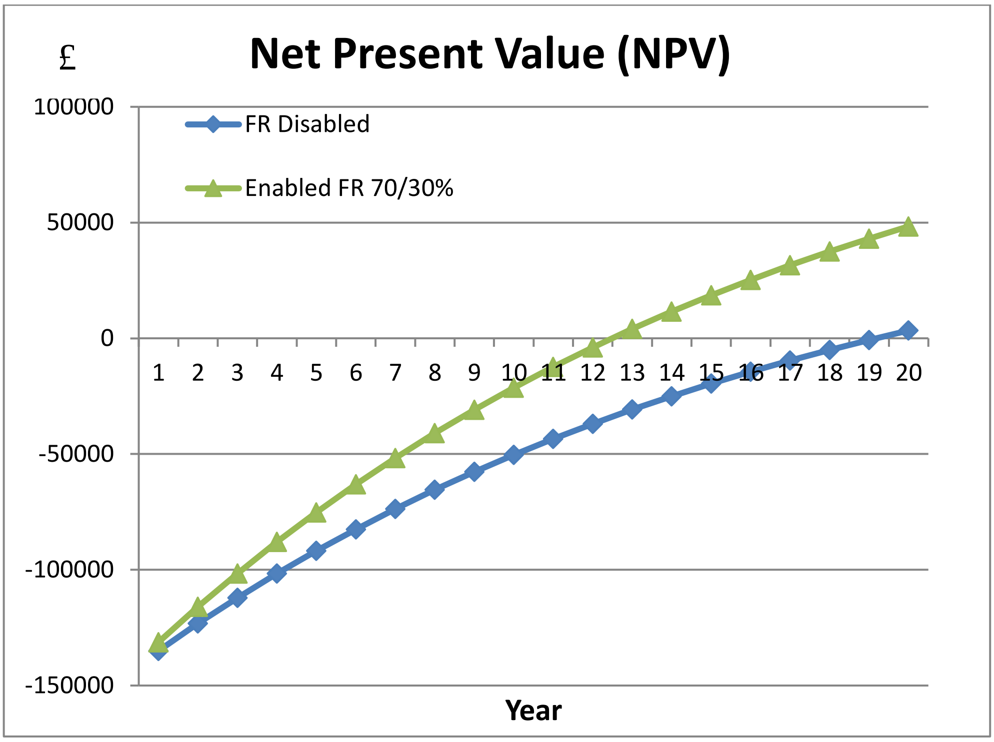


Fig 7.3 Net Present Value (NPV) comparison.

According to the presented results in Figure 7.3 the repayment period for the ESS with only achieving local objectives is twenty years, much longer than when the ACPP-EMS controller is used as part of the frequency regulation market when the repayment period for the investment is twelve years. In the first scenario the investment is not desirable.

As it clearly concluded small residential BESS trough the proposed novel architecture and the higher level novel ACPP-EMS controller developed, can provide a much higher benefit for both the electricity end users/owners of the system and DNOs through the combination of local objectives and frequency regulation services if the end users operate as an energy community.

7.3 Areas of further Improvement -Future Work

The results presented for the proposed novel control hierarchical framework and the novel ACPP-EMS higher level controller as part of the proposed control framework were executed with one lower level "community cell" as the ACPP-EMS controller controlled area. Furthermore, the real time community controller developed as part of the lower "community cell" level includes only EV charging management capabilities and other DSM techniques are neglected. Due to the above as the next steps for further testing and improving if required the capabilities of the higher level ACPP-EMS controller are:

1) The "community cell" controller should be tested with a more complex real time controller which incorporates greater DSM capabilities for an overall framework performance comparison.

2) New "community cells" should be incorporated at the lower level. By adding community cells to the existing one, the controlled area becomes larger and gives the opportunity to test and compare the performance of the ACPP-EMS controller with the already performed tests results.

3) Furthermore, the low level "community cell" used during this project consisted purely of residential buildings. A next step in the evolution and testing of the higher level ACPP-EMS is to incorporate as part of the low level controlled cells a number of different big non-residential loads the can be potentially encountered in urban areas. Typical examples of non-residential urban area loads than can be used are schools, hotels and universities.

4) The final step for testing the ACPP-EMS controller would be to test its performance with a lower level “community cell” consisting of a real, existing, community that is controlled by a real time low level controller able to follow profiling targets and with the ACPP-EMS controller following real Frequency Regulation Requests by the DNO. This test will validate the ability of the proposed novel controller to provide both local and “global” (frequency regulation) services as well as the functionality of the proposed framework.

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Appendix A

Indicators	Cost of import Energy (£)		Energy Import during Peak time (16:00-23:00)		Energy Import (kWh)		Energy Export (kWh)		Equivalent Cycles
ESS Charging from PV gen-Peak Disch used during expensive Peak time Period	87696		235137		495930		9741		186
ESS Charging from excess-Peak Disch. used during expensive Peak time Period	89922		259354		487078		927		34
Constant Year average Demand Target (59,01 KW)	77961		194431		498741		12143		262
Variable Target -ACPP-EMS	78737		207849		490392		4136		273

Average Energy Import During Peak Time Period

Year Peak Time 16:00-23:00) (HHB)	Excess PVg-Disch Peak time	PVg-Disch Peak time	Constant Power Target	Variable Target - ACPP-EMS
16:00-16:30	37.8	38.8	27.6	39.9
16:30-17:00	46.7	46.7	30.1	41.0
17:00-17:30	55.3	54.1	32.3	42.7
17:30-18:00	60.3	57.7	34.5	43.8
18:00-18:30	62.5	58.9	37.5	44.5
18:30-19:00	63.1	58.5	40.5	44.6
19:00-19:30	61.6	56.3	44.1	45.2
19:30-20:00	58.8	52.5	48.2	45.5
20:00-20:30	58.1	50.7	50.6	46.2
20:30-21:00	58.3	49.9	51.0	47.2
21:00-21:30	58.4	49.1	51.4	48.3
21:30-22:00	55.9	46.0	50.4	48.5
22:00-22:30	52.0	41.9	48.8	47.4
22:30-23:00	45.9	35.8	44.9	45.3

Appendix B

August	Price FR 31.4p/KWh			
		Cost of Import Energy(£)	Benefit from Frequency regulation(£)	Total Cost (£)
No ESS		7007	0	7007
350 KWh	100% L/0% D.FR	5644	99	5544
	90% L/10% D.FR	5660	172	5488
	80% L/20% D.FR	5718	249	5469
	70% L/30% D.FR	5796	317	5479
	60% L/40% D.FR	5906	385	5521
	50% L/50% D.FR	6049	455	5594
	40% L/60% D.FR	6152	484	5669
	30% L/70% D.FR	6292	518	5775
	20% L/80% D.FR	6431	548	5883
	10% L/90% D.FR	6554	559	5996
	0% L/100% D.FR	6675	557	6118

November	Price FR 31.4p/kWh			
		Cost of Import Energy(£)	Benefit from Frequency regulation(£)	Total Cost (£)
No ESS		9399	0	9399
350 KWh	100% L/0% D.FR	7983	142	7842
	90% L/10% D.FR	8081	265	7816

	80% L/20% D.FR	8165	399	7766
	70% L/30% D.FR	8274	545	7728
	60% L/40% D.FR	8405	649	7755
	50% L/50% D.FR	8530	787	7743
	40% L/60% D.FR	8629	833	7796
	30% L/70% D.FR	8749	874	7876
	20% L/80% D.FR	8881	908	7973
	10% L/90% D.FR	8911	930	7981
	0% L/100% D.FR	8904	937	7967

Year	Price FR 31.4p/kWh			
		Cost of Import Energy(£)	Benefit from Frequency regulations(£)	Total Cost (£)
No ESS		91996	0	91996
350 KWh	100% L/0% D.FR	76711	1388	75322
	90% L/10% D.FR	77576	2515	75061
	80% L/20% D.FR	78596	3778	74818
	70% L/30% D.FR	79723	4942	74782
	60% L/40% D.FR	81058	5976	75082
	50% L/50% D.FR	82356	7100	75256

	40% L/60% D.FR	83729	7777	75952
	30% L/70% D.FR	85270	8066	77204
	20% L/80% D.FR	86770	8306	78464
	10% L/90% D.FR	87687	8522	79165
	0% L/100% D.FR	88416	8612	79803

Year	Price FR 37.5p/kWh			
		Cost of Import Energy(£)	Benefit from Frequency Regulation(£)	Total Cost (£)
No ESS		91996	0	91996
350 KWh	100% L/0% D.FR	76756	1692	75064
	90% L/10% D.FR	77576	3042	74534
	80% L/20% D.FR	78596	4497	74099
	70% L/30% D.FR	79723	6011	73713
	60% L/40% D.FR	80986	7358	73628
	50% L/50% D.FR	82356	8575	73782
	40% L/60% D.FR	83729	9370	74359
	30% L/70% D.FR	85270	9825	75445
	20% L/80% D.FR	86770	10083	76686
	10% L/90% D.FR	87687	10345	77342
	0% L/100% D.FR	88416	10417	77999

Frequency Regulation Requests Number , Probability and Type								
Month		FRR – Maximise Demand		FRR – Maximise Demand (Probability)		FRR- Minimise Demand		FR- Minimise Demand (Probability)
Jan		20		0.14		11		0.21
Feb		17		0.12		8		0.15
Mar		12		0.09		4		0.08
Apr		6		0.04		4		0.08
May		9		0.06		1		0.02
Jun		3		0.02		1		0.02
July		7		0.05		1		0.02
Aug		8		0.06		2		0.04
Sept		10		0.07		4		0.08
Oct		16		0.11		7		0.13
Nov		15		0.11		5		0.09
Dec		18		0.13		5		0.09

Year	FRR 10% higher number			
		Cost of Import Energy(£)	Benefit from Frequency Regulation(£)	Total Cost (£)
No ESS		91996	0	91996
350 KWh	100% L/0% D.FR	76651	1607	75045
	90% L/10% D.FR	77486	2847	74639
	80% L/20% D.FR	78425	4212	74212
	70% L/30% D.FR	79562	5484	74079
	60% L/40% D.FR	80868	6790	74077
	50% L/50% D.FR	82202	7759	74443
	40% L/60% D.FR	83628	8569	75059
	30% L/70% D.FR	85107	8850	76258
	20% L/80% D.FR	86569	9113	77456
	10% L/90% D.FR	87428	9356	78072
	0% L/100% D.FR	88162	9463	78699

Appendix C

NPV			
T(Years)	FR Disabled	Enabled FR	Enabled FR 70/30%
1	-135003	-131785	-131275
2	-123224	-116973	-115983
3	-112122	-103013	-101570
4	-101659	-89855	-87985,5
5	-91797,3	-77453,9	-75182,2
6	-82502,5	-65765,7	-63115
7	-73742,2	-54749,5	-51741,5
8	-65485,4	-44366,7	-41022
9	-57703,4	-34580,8	-30918,7
10	-50368,8	-25357,6	-21396,3
11	-43455,9	-16664,6	-12421,4
12	-36940,4	-8471,35	-3962,5
13	-30799,5	-749,192	4010,101
14	-25011,7	6528,997	11524,33
15	-19556,6	13388,74	18606,54
16	-14415,2	19854,1	25281,58
17	-9569,35	25947,74	31572,85
18	-5002,1	31691,05	37502,41
19	-697,448	37104,15	43091,07
20	3359,721	42206,04	48358,42

Appendix D

One Year Peak time (16:00-23:00)					
No control	EV Charging Control	ACPP-EMS/NO EV Charging Control		ACPP-EMS/EV Charging Control*	
Import Energy(kWh)	Import Energy(kWh)	ESS size(kWh)	Import Energy(kWh)	ESS size(kWh)	Import Energy(kWh)
271410	232697	350	207309	350	189139
				300	194792
				250	201570
				200	208989
				150	216633
				100	224270
				50	230275