SYSTEMATIC APPROACHES FOR SYNTHESIS, DESIGN AND OPERATION OF BIOMASS-BASED ENERGY SYSTEMS

VOLUME 1

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ABSTRACT

A biomass-based energy system (BES) is a utility facility which produces cooling, heat and power simultaneously from biomass. By having a BES installed on-site, industrial processes can reduce energy costs by locally producing heat, cooling and power for process and work place requirements. However, several barriers have hindered development of BESs in the energy industry. These barriers include doubts over its operational uncertainties (e.g., seasonal biomass supply, equipment reliability, etc.), the misconception that generating energy from biomass is only a marginal business and the lack of successful cooperative partnerships within the industry. According to literature, such barriers are due to the lack of frameworks that address design aspects and demonstrate the economic viability of a BES.

This thesis presents systematic approaches and frameworks to design a BES. These approaches emphasise on integrating synthesis, design and operation decision making for a BES during its preliminary design phase. Firstly, a systematic approach is presented to synthesise a BES considering seasonal variations in biomass supply and energy demand. In this approach, a multi-period optimisation model is formulated to perform technology and design capacity selection by considering seasonal variations in biomass supply and energy demand profiles. This approach is then extended to systematically allocate equipment redundancy within the BES in order to maintain a reliable supply of energy. In this approach, *k*-out-of-*m* system modelling and the principles of chance-constrained programming are integrated in a multi-period optimisation model to simultaneously screen technologies based on their respective equipment reliability, capital and operating costs. The model also determines equipment capacities, along with the total number of operating (and stand-by) equipment based on various anticipated scenarios in a computationally efficient manner. Following this, a systematic approach is developed to simultaneously screen, size and allocate redundancy within a BES considering its operational strategies (e.g., following electrical load or following thermal load).

Subsequently, a systematic framework on Design Operability Analysis (DOA) is developed to analyse BES designs in instances of failure. This framework provides a stepwise procedure to evaluate proposed BES designs under scenarios of disruption and analyse their true feasible operating range. Knowledge of the feasible operating range enables designers to determine and validate if a BES design is capable of meeting its intended operations. Following this, a systematic Design Retrofit Analysis (DRA) framework is presented to debottleneck and retrofit existing BES designs in cases where energy demands are expected to vary in the future. The presented framework re-evaluates an existing BES design under disruption scenarios and determines its real-time feasible operating range. The real-time feasible operating range will allow designers to determine whether debottlenecking is required. If debottlenecking is required, the framework provides systematic debottlenecking and retrofit guidelines for BES designs. The design of a BES is then extended further to consider its interaction in an eco-industrial park (EIP). Since heat, cooling and power are essentially required in most industrial processes, a BES can be more economically attractive if synthesised for an EIP. As such, an optimisation-based negotiation framework is developed to analyse the potential cost savings allocation between participating plants in an EIP coalition. This framework combines the principles of rational allocation of benefits with the consideration of stability and robustness of an EIP coalition to changes in cost assumptions. Lastly, possible extensions and future opportunities for this research work are highlighted at the end of this thesis.

PUBLICATIONS

Refereed journals:

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Andiappan, V., Tan, R. R., Ng, D. K. S., (2016). An Optimisation-based Negotiation Framework for Energy Systems in an Eco-Industrial Park. *Journal of Cleaner Production*. 129, pp 496 – 507.

Andiappan, V., Ng, D. K. S., (2016). Synthesis of Tri-generation Systems: Technology Selection, Sizing and Redundancy Allocation based on Operational Strategy. *Computers & Chemical Engineering* (in press).

Andiappan, V., Ng, D. K. S., Tan, R. R. Systematic Framework for Biomass-based Tri-generation Systems – Part 1: Design Operability Analysis (DOA). *Chemical Engineering Research and Design* (in review).

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Book chapters

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Conference presentations:

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Andiappan, V., Tan, R. R., Ng, D. K. S., (2014). Systematic Approach for Profit Allocation among Energy Systems within an Eco-Industrial Park. *Asia Biohydrogen and Biorefinery Symposium 2014 (ABB 2014)*, 16 – 18 December 2015, Malacca, Malaysia (in proceeding).

Andiappan, V., Tan, R. R., Aviso, K. B., Ng, D. K. S., (2015). Synthesis of Biomass-based Trigeneration Systems with Reliability Aspects. *Computer Aided Chemical Engineering*. 37, pp 2243 – 2248. *12th International Symposium on Process Systems Engineering and 25th European Symposium on Computer Aided Process Engineering 2015 (PSE/ESCAPE 2015)*, 31 May – 4 June 2015, Copenhagen, Denmark (in proceeding).

Andiappan, V., Tan, R. R., Ng, D. K. S., (2015). Systematic Allocation of Cost Savings among Energy Systems in an Eco-Industrial Park. *Chemical Engineering Transactions*. 45, pp 1657 – 1662. *3rd Postgraduate*

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Tan, R. R., Ng, R. T. L, **Andiappan, V.,** Wan, Y. K., Ng, D. K. S., (2015). An Optimization-based Cooperative Game Approach for Allocation of Costs and Benefits in Interplant Process Integration. *Chemical Engineering Transactions*. 45, pp 403 – 408. *Conference Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction 2015 (PRES' 15)*, 24 – 26 August 2015, Sarawak, Malaysia (in proceeding).

Andiappan, V., Tan, R. R., Ng, D. K. S., (2015). An Optimisation-based Negotiation Framework for Energy Systems in an Eco-Industrial Park. *International Conference of Advanced Energy Research 2015 (ICAER 2015)*, 15 – 17 December 2015, Mumbai, India (in proceeding).

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LIST OF ABBREVIATIONS

BP	British Petroleum
BES	Biomass-based energy system
CHP	Combined heat and power
CCHP	Combined cooling, heat and power
CCP	Chance-constrained programming
CPKO	Crude palm kernel oil
CPO	Crude palm oil
DLF	Dried long fibre
DME	Dimethyl-ester
DOA	Disruption operability analysis
DRA	Disruption retrofit analysis
DSA	Disruption scenario analysis
EA	Evolutionary algorithm
EFBs	Empty fruit bunches
EMOA	Evolutionary multi-objective algorithm
EIA	Energy Information Administration
EIP	Eco-industrial park
EPU	Economic Planning Unit
FEL	Following electrical load
FFBs	Fresh fruit bunches
FFA	Free fatty acid
FORA	Feasible operating range analysis
FT-fuel	Fischer-Tropsch fuel
FTL	Following thermal load

GA	Genetic algorithm
GHG	Greenhouse gas
HEN	Heat exchanger network
HPS	High pressure steam
HRSG	Heat recovery steam generator
IE	Industrial ecology
IIM	Inoperability input-output modelling
IIR	Incremental Investment Return
LP	Linear programming
LPS	Low pressure steam
MEIH	Malaysian Energy Information Hub
MeOH	Methanol
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear programming
MPS	Medium pressure steam
MOO	Multi-objective optimisation
NBS2020	National Biomass Strategy 2020
NLP	Non-linear programming
NREL	National Renewable Energy Laboratory
PBB	Palm-based biorefinery
PEIP	Palm-based eco-industrial park
PKS	Palm kernel shell
PMF	Palm mesocarp fibre
POM	Palm oil mill
POME	Palm oil mill effluent

POPC	Palm oil processing complex
PSE	Process System Engineering
SOO	Single-objective optimisation
VHPS	Very high pressure steam

LIST OF SYMBOLS

Indices

i	Index for biomass
j , j'	Index for technologies
p	Index for primary products
p'	Index for final products
q	Index for component balance of biomass i
q'	Index for component balance of primary product p
n, n'	Index for available design capacities for technology
s	Index for scenarios
e	Index for energy
w	Index for source/raw material stream
u	Index for plants
z	Index for coalitions

Variables

F_i^{BIO}	Flow rate of biomass i
f_{iq}^{BIO}	Component flow rate of biomass i
F_{ij}^{I}	Flow rate of biomass i to technology j
f_{qj}^{I}	Component flow rate of biomass i to technology j
F_{jp}^{I}	Production rate of primary product p at technology j
F_p	Total production rate of primary product p at technology j
F_p^{Ret}	Total flow rate of primary product p recycled

F^{I}_{pj}	Flow rate of *p* recycled to technology *j*
$F^{\mathrm{I}}_{p'j}$	Flow rate of *p'* recycled to technology *j*
$F^{\mathrm{II}}_{pj'}$	Flow rate of primary product *p* to technology *j'*
$f^{\mathrm{II}}_{q'j'}$	Component flow rate of product *p* to technology *j'*
$F^{\mathrm{II}}_{j'p'}$	Production rate of final product *p'* at technology *j'*
$F_{p'}$	Total production rate of final product *p'* at technology *j'*
$F^{\mathrm{Ret}}_{p'}$	Total flow rate of final product *p* recycled
$F^{\mathrm{II}}_{p'j'}$	Flow rate of *p'* recycled to technology *j'*
E^{Gen}_{e}	Total energy generated by technology *j* and *j'*
E^{Con}_{e}	Total energy consumption for technology *j* and *j'*
E^{Imp}_{e}	Total external energy imported
E^{Exp}_{e}	Total excess energy exported
E^{Demand}_{e}	Total energy demand
EP	Economic performance
GP	Total gross profit
CAP	Total capital cost
$ACAP$	Total annualised capital cost
MAC	Total maintenance cost
TAC	Total annualised cost
OP_s	Total operating cost for strategy *s*
z_{jn}	Number of units of design capacity *n* selected
$z_{j'n'}$	Number of units of design capacity *n'* selected

R_{jn}	Reliability of design capacity *n* in technology *j*
$R_{j'n'}$	Reliability of design capacity *n'* in technology *j'*
m_{jn}	Number of units of design capacity *n* installed in technology *j*
$m_{j'n'}$	Number of units of design capacity *n'* installed in technology *j'*
x_j	Operating capacity of process unit *j* (fraction)
y_w	Net flow of stream *w* from plant
BCR	Benefit cost ratio (fraction)
C_w^{Stream}	Unit cost of stream *w*
CAP^{Add}	Total annualised capital cost of additional technologies
CS_u	Total cost savings of plant *u*
CS_z	Cost savings of a partnership
CS_w	Cost savings of a partnership without plant *u*
C_{au}^{EIP}	Cost of material from EIP
C_{au}^{Ext}	Cost of material from external facilities
GP_u	Gross profits of plant *u*
SA_u	Allocation of cost savings to plant *u*
SI_u	Symbiosis Investment of plant *u*
cf_u	Fraction of raw material costs in plant *u*
DC_u	Distribution coefficient of each plant *u*
ADC_u	Asymmetric distribution coefficient of each plant *u*
$ADC_u^{\max}$	Maximum limit for asymmetric distribution coefficient of each plant *u*
$ADC_u^{\min}$	Minimum limit for asymmetric distribution coefficient of each plant *u*

Parameters

θ_{iq}	Composition *q* of biomass *i*
$\theta_{pq'}$	Composition *q'* of product *p*
X^{I}_{qjp}	Component mass conversion of biomass *i*
$X^{II}_{q'j'p'}$	Component mass conversion of primary product *p*
V^{I}_{qje}	Component energy conversion at technology *j*
$V^{II}_{q'j'e}$	Component energy conversion at technology *j'*
Y^{I}_{ejp}	Component energy consumption conversion at technology *j*
$Y^{II}_{ej'p'}$	Component energy consumption conversion at technology *j'*
AOT	Annual operating time
C^{BIO}_{i}	Cost of biomass *i*
$C_{p'}$	Revenue from final product *p'*
C^{Imp}_{e}	Purchase cost of importing energy
$C^{Grl}_{p'}$	General expenses for producing final product *p'*
C^{Grl}_{e}	General expenses for producing energy *e*
C^{Exp}_{e}	Selling cost of exporting excess energy
C_{jn}	Capital cost for technology *j*
$C_{j'n'}$	Capital cost for technology *j'*
C^{Main}_{jn}	Maintenance cost of design capacity *n* for technology *j*
$C^{Main}_{j'n'}$	Maintenance cost of design capacity *n'* for technology *j'*
α_s	Fraction of occurrence for scenario *s*
CRF	Capital recovery factor
F^{Design}_{jn}	Available design capacity for technology *j*

$F_{j'n'}^{Design}$	Available design capacity for technology *j'*
r	Discount rate
t^{max}	Operation lifespan
P_{jn}	Reliability of design capacity *n* in technology *j*
$P_{j'n'}$	Reliability of design capacity *n'* in technology *j'*
R_{jn}^{Min}	Minimum reliability level of design capacity *n* in technology *j*
$R_{j'n'}^{Min}$	Minimum reliability level of design capacity *n'* in technology *j'*
a_{wj}	Output of stream *w* from process unit *j* at the baseline state
b_j	Binary variable indicating operation (b_j = 1) or non-operation (b_j = 0) of process unit *j*
x_j^L	Lower limit of operability of process unit *j* (fraction)
x_j^U	Upper limit of operability of process unit *j* (fraction)
C_j^{Cap}	Annualised capital cost of technology/process unit *j* at the baseline state per unit main product

CHAPTER 1

INTRODUCTION

1.1 Background

Fossil fuel is widely utilised as a source of energy production. According to a statistical review released by British Petroleum (BP) in 2013, 87% of the world's energy demand is met by consumption of fossil fuel such as oil, natural gas and coal (Figure 1.1). Such large percentage evidently indicates a high global dependency on fossil fuel as a primary source of energy. Despite its vast usage, fossil fuel is regarded as a key contributor to greenhouse gas (GHG) emissions such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (Environmental Leader, 2013). As shown in Figure 1.2, the continuous consumption of fossil fuel has caused CO_2 levels in 2008 to increase by 16 times since 1900 (Boden et al., 2012).

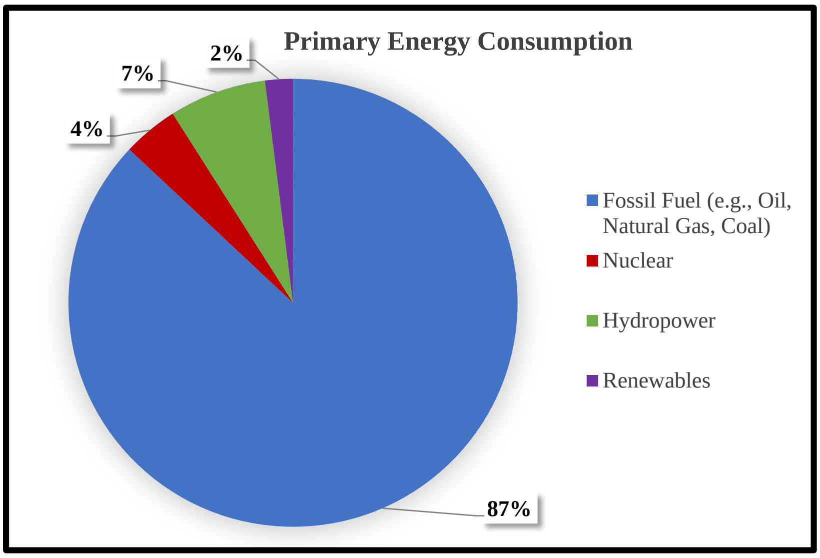

Figure 1.1: Primary Energy Consumption (British Petroluem, 2013)

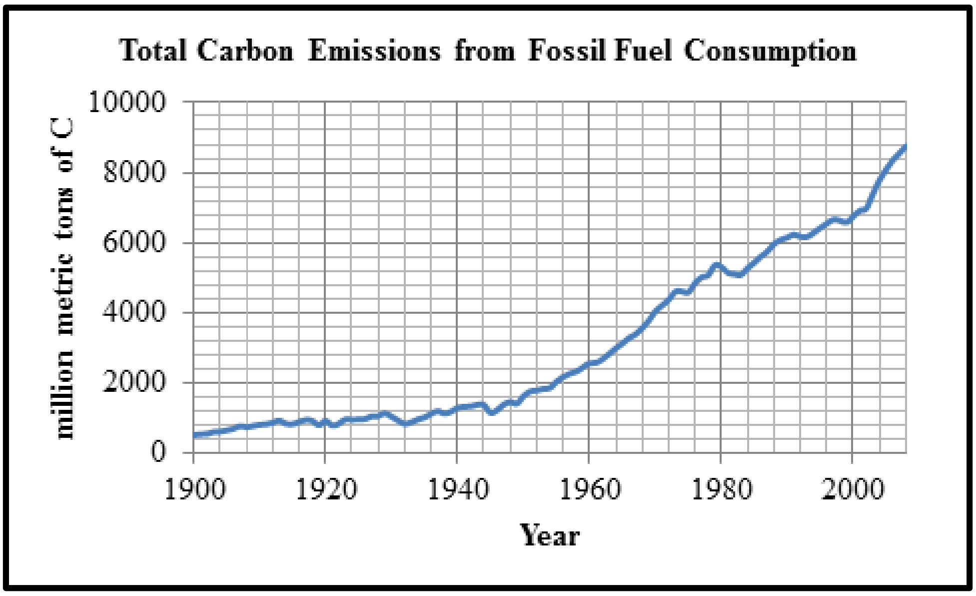

Figure 1.2: Total Carbon Emissions from Fossil Fuel Consumption (Boden et al., 2012)

Such increase has led to the need for a more environmental friendly alternative to fossil fuel. In this respect, several research works have identified biomass as a sustainable source that is able to reduce the global dependency on fossil fuel (Bridgwater, 2003; Greenwise, 2011; Naik et al., 2010; Schlamadinger et al., 1997). According to the National Renewable Energy Laboratory (NREL), biomass is defined as energy contributed by plants and plant-based materials such as food crops, woody and grassy plants, forestry as well as agricultural residues (NREL, 2011). Since biomass originates from plant based material, biomass has the potential to cut down CO_2 emissions. This is because the plants in which biomass originate from also use CO_2 during photosynthesis (Naik et al., 2010). As a result, there is no net increase of CO_2 in the atmosphere, making biomass more environmentally friendly as compared to their fossil fuel counterparts (Hill et al., 2006). Such potential could mean that agricultural countries such as Malaysia can benefit from utilising its available biomass for energy production.

According to a report by United States Energy Information Administration (EIA) in 2014, fossil fuels such as coal and natural gas made up about 86% of Malaysia's 29.1 GW installed power generation capacity and 92% of the country's power output in 2012. In fact, the Malaysian Energy Information Hub (MEIH) anticipates that the country’s power demands will grow by more than 3% at least through 2020 (EIA, 2014). However, such growth in power demands raises concerns as Malaysia has been facing shortages in natural gas since 2011. This, coupled with concerns on rising emissions, has driven Malaysia to diversify its portfolio of power generation fuels and reduce its CO_2 levels 40% by 2020 (compared to levels in 2005). As a result, National Biomass Strategy 2020 (NBS2020) was formulated in 2013 by the Malaysian government to promote the use of agricultural biomass wastes for high value products.

NBS2020 identified Malaysia’s palm oil sector as potential starting point as it is the largest biomass generating sector in the country. This is evident as previous reports claim about 83 million dry tonnes of palm-based biomass was generated in 2010. Reports also suggest that the amount of biomass generated is expected to rise further to around 100 million dry tonnes by 2020 (Ng, 2013). Such increase led Malaysia’s Economic Planning Unit (EPU) to devise the recent 11th Malaysia Plan in 2015. Among its several focus areas, the 11th Malaysia Plan aims to encourage implementation of green technologies such as biomass energy systems in the palm oil industry. However, the successful realisation of the aims outlined by NBS2020 and the 11th Malaysia Plan will rely upon strong collaboration among many government agencies as well as biomass owners. The following sub-sections reviews the energy potential of palm-based biomass, along with latest developments and challenges faced in implementing biomass energy systems.

1.1.1 Energy Potential in Palm Oil Industry

Oil palm, also known as *Elaeis guineensis* Jacg., is a unique crop that produces two distinct types of oils: crude palm oil (CPO) and crude palm kernel oil (CPKO) (Malaysian Palm Oil Council, 2012). Palm oil is obtained from the mesocarp while palm kernel oil is obtained from the seed or kernel of the oil palm fresh fruit bunches (Abdullah and Sulaiman, 2013). These oils are used for different applications ranging from food applications like cooking oil and to non-food applications such as soap, cosmetics and detergents (Malaysian Palm Oil Council, 2006). With such applications, palm oil became the most consumed vegetable oil accounting for 33% of the world's vegetable oil consumption in 2011 (American Soybean Association, 2014).

CPO and CPKO are extracted from fresh fruit bunches (FFBs). FFBs are harvested and collected from oil palm plantations and undergo an extraction process in a palm oil mill (POM) to produce CPO and CPKO. At the same time, the extraction process generates palm-based biomass as waste by-products. These biomass include empty fruit bunches (EFBs), palm oil mill effluent (POME), palm mesocarp fibre (PMF) and palm kernel shell (PKS). For every tonne of FFB, 23% EFB, 14 – 15% PMF, 6 – 7% PKS and 60 – 70% POME are generated as waste products (Husain et al., 2002; Zafar, 2012). According to literature (Kelly-Yong et al., 2007; Yusoff, 2006), these palm-based biomass residues contain useful amount of energy which can be recovered for energy production. The energy content of the aforementioned palm-based biomass is summarised in Table 1.1.

Table 1.1: Calorific Values for Palm-based Biomass (Nasrin et al., 2008)

Palm-based Biomass	Calorific Value
EFB	18,838 kJ/kg
PMF	19,068 kJ/kg
PKS	20,108 kJ/kg
POME	22,000 kJ/m^3

Based on the calorific values shown in Table 1.1, it can be concluded that recovering energy from these biomass residues would enable POMs to harness high amounts of renewable energy from sources generally regarded as waste products (Moorthy, 2014). If palm-based biomass is utilised for energy production, the importation of energy and environmental impacts within the industry can be minimised (Abdullah and Sulaiman, 2013). Section 1.1.2 discusses current practices implemented to utilise palm-based biomass in the palm oil industry.

1.1.2 Latest Developments in Biomass Energy Systems

In current practice, most POMs are already utilising palm-based biomass in co-generation systems to generate heat and power. *Co-generation*, also known as combined heat and power (CHP) is where heat and power are produced simultaneously from a single fuel source (Combined Heat and Power Association, 2014). In such system, very high pressure steam (VHPS) is produced through combustion of PKS and PMF in water tube boilers. VHPS is then reduced in steam turbines to generate power. In addition, steam is extracted from different steam headers to provide heating energy for process heating in the POM (e.g., steriliser, digester) (Abdullah and Sulaiman, 2013).

Aside from PKS and PMF, EFBs are distributed to surrounding estates for mulching activities as its high moisture content (about 60%) forbids it from being used a boiler fuel. However, EFB Mulching is not a widespread activity as some mills face high transportation costs, do not own plantations and lack labour power (Malaysian Danish Environmental Cooperation Programme, 2005; Ng, 2013). As an alternative, some mills have developed EFB power plants with boilers specifically designed for the combustion of EFBs to produce energy (Ng, 2013).

Meanwhile, POME is conventionally treated in a sequence of aerobic and anaerobic ponds to reduce its high biochemical oxygen demand (BOD) and chemical oxygen demand (COD) levels, prior to being discharged into water (Chin et al., 2013). At the same time, POME treatment produces biogas, which contains 65% of CH_4 and 35% of CO_2. Since biogas contains mostly CH_4, it is clear that current practices are wasting a potential energy source (Chin et al., 2013). With this in mind, mill operators are considering several methods to trap and utilise the biogas produced. Biogas produced from POME can either be trapped within a thick sheet covering existing anaerobic treatment ponds or within anaerobic digesters (Abdullah and Sulaiman, 2013; Ng, 2013). The trapped biogas can then be purified and supplied to gas engines or gas turbines for power generation. Alternatively, the purified biogas can be used as fuel for fired tube boilers to generate heat and/or power for mill operations (Natural Resources Defense Council, 2014; Ng, 2013; Probiopol, 2014).

Based on the aforementioned practices, it can be noted that there are several alternatives to utilise palm-based biomass residues. However, recent developments suggests that mill operators are keen to extend mill operations to several downstream processes (discussed further in Section 1.1.3). Unfortunately, current practices in the palm oil industry may not be sufficient to meet the demands of extending mill operations. In this respect, there is a need to further develop biomass energy systems in the industry. As such, the following section discusses further on the prospects for biomass energy systems development.

1.1.3 Prospects for Biomass Energy Systems

As mentioned previously, existing co-generation systems in the palm oil industry allow palm oil mills to operate in an energy self-sustained manner (Moorthy, 2014). However, recent developments suggests that mill operators are looking to extend mill operations to several downstream processes such as CPO refining (Malaysian Palm Oil Council, 2006), mulching activities (Ng, 2013), production of bio-fertiliser (Malaysian Innovation Agency (AIM), 2013). Furthermore, there is a growing number of operators venturing into EFB pelletisation, EFB briquetting and production of dried long fibre (DLF) from EFB (Ng et al., 2012; Reeb et al., 2014). This would mean that existing palm oil mills would require higher amount of energy for daily operations.

Conventionally, palm oil mills use high amounts of heat for the palm oil extraction process (e.g., in sterilisation and digestion stages) compared to power (e.g., for pumps, conveyors, motors, etc.). Since the power to heat demand ratio of the process is typically low, co-generation systems are able to generate additional power within the heat required for mill operations. The additional power can then be distributed to downstream processes and/or be exported to the grid.

Apart from heat and power, some of the aforementioned downstream processes require cooling energy. For instance, CPO refining processes require chilled water for process cooling (Malaysian Palm Oil Council, 2006). Besides, agricultural production (e.g., mushroom production) would require chilled water for space cooling (Boyle, 2011). This leads to the possibility of setting up tri-generation systems, otherwise known as combined cooling, heat and power (CCHP) systems.

Tri-generation is an extension of co-generation, where thermally fed absorption chillers or mechanical chillers are utilised to produce cooling energy (Chicco and Mancarella, 2009). With the emergence of downstream processes, the implementation of tri-generation systems would be an attractive proposition for the palm oil industry. Such system would act as a central utility system that provides cooling, heating and power to its surrounding processing facilities. Such implementation is synonymous with the concept of eco-industrial parks (EIPs). EIP is defined as a community of manufacturing, industrial and service businesses co-located on a common property. The aim of an EIP is to collaborate in managing resources of participating facilities to improve overall economic performance (Lowe, 2001). Such opportunity is lucrative, as tri-generation systems are able to turn waste products from existing palm oil mills into a useful energy for its neighbouring facilities. In the case where there is grid access, tri-generation systems can operate as decentralised energy systems by exporting surplus power to the national grid to generate more revenue (Abdullah and Sulaiman, 2013; Leete, 2007; Moorthy, 2014).

Whilst the concept of a biomass energy system is promising, there are a number of challenges which have hindered its development. Section 1.1.4 discusses further on these challenges.

1.1.4 Challenges in Biomass Energy Systems

The barriers in the development of biomass energy systems are identified as the following;

- Availability of fuel supply – Stakeholders face difficulties in securing long term biomass supply, due to its seasonal nature. Such issue raises concerns on whether there would be sufficient biomass supply to meet energy demands (Leete, 2007; Umar et al., 2014, 2013a).
- Reliability and availability of equipment – Regular maintenance of crucial equipment is required to prevent forced outages. However, crucial equipment that are frequently off-line for maintenance would disrupt a reliable supply of energy (Leete, 2007).
- General conception that generation and sale of energy from biomass is a side business, hence disregarding its economic potential in the energy marketplace (Leete, 2007; Umar et al., 2014, 2013b).

- Lack of successful partnerships within the industry – There are limited examples of interactive frameworks that initiate industrial cooperation in the Malaysian biomass industry to improve credibility of biomass energy production (Joseph, 2015; Umar et al., 2014, 2013b). Although the agreement for a Biomass Joint Venture Cluster project in Lahad Datu, Sabah was signed in 2013, its success remains to be seen.

1.2 Aim of Research

According to literature (Hiremath et al., 2007; Hobbs, 1995; Umar et al., 2013b; Yılmaz and Selim, 2013), the challenges mentioned in Section 1.1.4 are due to the lack of systematic approaches to design biomass energy systems and to analyse their economic viability in the energy marketplace. As such, this research aims to contribute to the body of knowledge by developing systematic approaches needed to address the challenges mentioned in Section 1.1.4.

1.3 Objectives of Research

The aim of this research is accomplished by developing systematic approaches with the objective to;

i. Consider operational issues in biomass-based energy systems such as variations in biomass supply, equipment reliability, operating strategies and future energy demand changes.

ii. Investigate economic viability of biomass tri-generation systems in the energy marketplace.

1.4 Thesis Outline

Chapter 1 introduced the background of the problem faced in the development of biomass energy systems along with the aim and objectives of this thesis. The remaining parts of this thesis is described in the following;

Chapter 2 Literature Review

Chapter 2 presents a critical review on the potential energy systems and various state-of-the-art approaches available for use. This is followed by a review of the systematic approaches developed in the past that consider and address the challenges mentioned in Section 1.1.4. At the end of this chapter, research gaps and opportunities for improvement are identified as motivation for this research work/thesis.

Chapter 3 Research Scopes and Methodology

Based on the research gaps highlighted in Chapter 2, several research scopes are proposed in Chapter 3. These research scopes are addressed with a systematic research methodology is discussed in detail at the end of Chapter 3.

Chapter 4 Synthesis of Biomass-based Energy Systems with Variations in Biomass Supply and Energy Demand

In Chapter 4, a systematic approach is developed to synthesise and design of a biomass-based energy system (BES) based on seasonal variations in biomass supply and energy demand. A multi-period optimisation approach is developed consider variations in raw material supply and corresponding energy demands. To illustrate the proposed approach, a tri-generation system with palm-based biomass as feedstock is solved in this chapter.

Chapter 5 Synthesis and Optimisation of Biomass-based Energy Systems with Reliability Aspects

The approach presented in Chapter 4 is then extended to consider reliability aspects of the BES in Chapter 5. In Chapter 5, a novel systematic approach is presented to synthesise a reliable grassroots BES design considering allocation of equipment redundancy. The presented approach considers the possibility of installing either large capacity equipment or multiple smaller capacity units based on their unique equipment reliabilities. Two case studies are then solved to illustrate this developed approach.

Chapter 6 Synthesis of Biomass-based Energy Systems: Technology Selection, Sizing and Redundancy Allocation based on Operational Strategy

Chapter 6 extends the work developed in Chapter 5 to consider the operational strategy of the BES. In this chapter, a systematic approach is developed to to synthesise a BES robust towards operating strategies considered. This approach simultaneously performs selection of technology, the sizing of equipment and redundancy allocation to cope with equipment failure within the system based on operational strategies considered. A palm biomass-based tri-generation case study is solved to illustrate the proposed approach.

Chapter 7 Systematic Approach for Design Operability Analysis (DOA) of Biomass-based Energy Systems

This chapter presents a systematic Design Operability Analysis (DOA) framework for a BES. The developed framework is a systematic procedure that can be used by designers to analyse performance of BES designs during failures. The framework evaluates proposed BES designs under disruption scenarios and analyses their true feasible operating range. Based on the feasible operating range, designers can determine if a proposed BES design is capable of meeting its intended operations. To illustrate the developed framework, analysis of a palm BES design from Chapters 5 is demonstrated.

Chapter 8 Systematic Approach for Design Retrofit Analysis (DRA) of Biomass-based Energy Systems

This chapter presents a systematic framework to debottleneck existing BES designs in the case where future energy demand expansion plans are required. This framework re-evaluates the capability of an existing BES to cope with disruption scenarios and determine its real-time feasible operating range. In this respect, designers can make informed decisions on whether debottlenecking and retrofit actions for an existing BES are required. If debottlenecking is necessary, the framework provides systematic debottlenecking and retrofit procedures for the BES design. To illustrate the developed framework, the debottlenecking of the BES from Chapter 5 is demonstrated.

Chapter 9 An Optimisation-based Negotiation Framework for Energy System in an Eco-industrial Park

Following Chapters 4 – 8, an optimisation-based negotiation framework is presented to analyse the economic viability of a BES in potential coalitions with neighbouring facilities within an EIP. This framework combines the principles of rational allocation of benefits with the consideration of stability and robustness of the coalition to changes in cost assumptions. To illustrate the proposed framework, a case study on energy systems in a palm oil eco-industrial park (PEIP) is presented in Chapter 8.

Chapter 10 Conclusions, Contributions and Future Works

In Chapter 10, the contributions of this thesis are mapped to provide designers a complete overview of the systematic approaches developed. Lastly, future research works are enumerated at the end of Chapter 10 to provide further opportunities on improving the completeness of the systematic approaches developed in this thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In Chapter 2, a literature review is provided on the existing systematic approaches for the synthesis of energy systems. Firstly, Section 2.2 introduces the concept of energy systems and highlights the need for systematic tools to address problems related to energy systems. Next, a review is provided on Process Systems Engineering (PSE) approaches (Section 2.3), mainly mathematical optimisation approaches (Section 2.4) used to form systematic tools in addressing energy system synthesis. Then, Section 2.5 reviews the systematic approaches for the synthesis of energy systems, highlighting the importance of adapting an integrated approach over a hierarchical one. Following this, Section 2.6 discusses the importance of considering reliability aspects in design and reviews the works done in this respect. Section 2.7 reviews approaches concerning design validation, debottlenecking and retrofit. In Section 2.8, a review is provided on the concept of eco-industrial parks and the works related. Based on the given review, research gaps are identified along with the contribution of this research work (Section 2.9).

2.2 Energy Systems

Energy systems typically operate as co-generation or tri-generation systems. Co-generation systems produce heat and power are simultaneously from a single fuel source (Figure 2.1) (Chicco and Mancarella, 2009). In co-generation, high pressure steam is produced through combustion of fuel in boilers. The pressure of the produced steam is then reduced in steam turbines to generate power. In addition, steam is extracted from different steam headers to provide heating energy based on process requirements (Al-Sulaiman et al., 2011). Meanwhile, tri-generation is an extension of co-generation where heat or power is further utilised in either mechanical chillers or thermally fed absorption chillers to produce cooling energy (e.g., chilled water) for space/process cooling (Chicco and Mancarella, 2009).

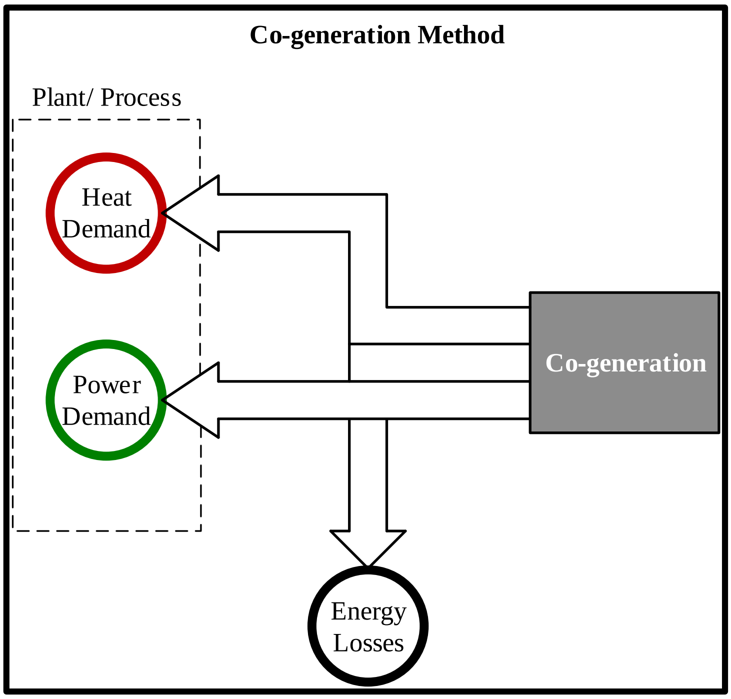

Figure 2.1: Co-generation Method for Heat and Power Generation (Combined Heat and Power Association, 2014)

Mechanical chillers work on the principle of vapour compression cycle (Chartered Institution of Building Services Engineers, 2012). Such cycle typically consists of four components which include evaporator, compressor, condenser and expansion valve (as shown in Figure 2.2) (Bengtson, 2011). Based on Figure 2.2, heat is extracted from chilled water and is added to the refrigerant at constant pressure. Both refrigerant and chilled water do not mix and are separated by a solid wall in the evaporator (Bengtson, 2011). The refrigerant then leaves the evaporator as vapour and is compressed by a compressor (which requires power input) to high pressure and temperature. Then, the compressed refrigerant vapour is then sent to a condenser, where its heat is rejected to the outside cooling medium (e.g., cooling water, air, etc.). The refrigerant then leaves the condenser as liquid and is expanded in an expansion valve, where its pressure and temperature is reduced to the level of the evaporator (Haywood, 1980; Whalley, 1992). This cycle repeats again to continuously produce chilled water at the evaporator section.

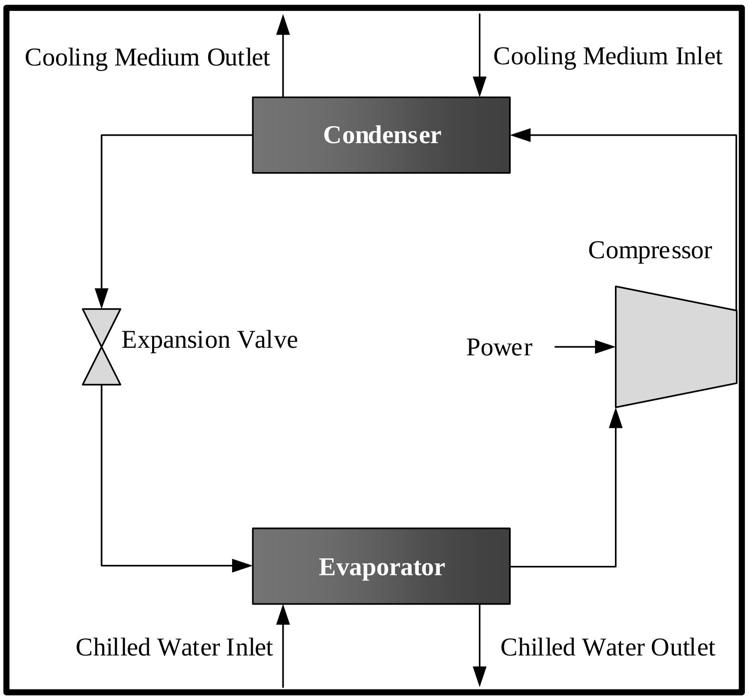

Figure 2.2: Vapour Compression Cycle (Bengtson, 2011)

Unlike mechanical chillers, the working principle for absorption chillers is the absorption cycle (Chartered Institution of Building Services Engineers, 2012). In the absorption cycle (shown in Figure 2.3), the compressor in the vapour compression cycle is replaced with a chemical cycle. This chemical cycle consists of an absorber, pump and regenerator (Rafferty, 1998). Instead of compressing the refrigerant vapour exiting the evaporator like in the vapour compression cycle, the absorption cycle dissolves the vapour in a liquid (called the absorbent) (Srikhirin et al., 2001). The solution is then pumped to a higher pressure (with much less power input than of a compressor) and uses heat input, typically waste heat (Goodell, 2006) to evaporate the refrigerant vapour out of the solution.

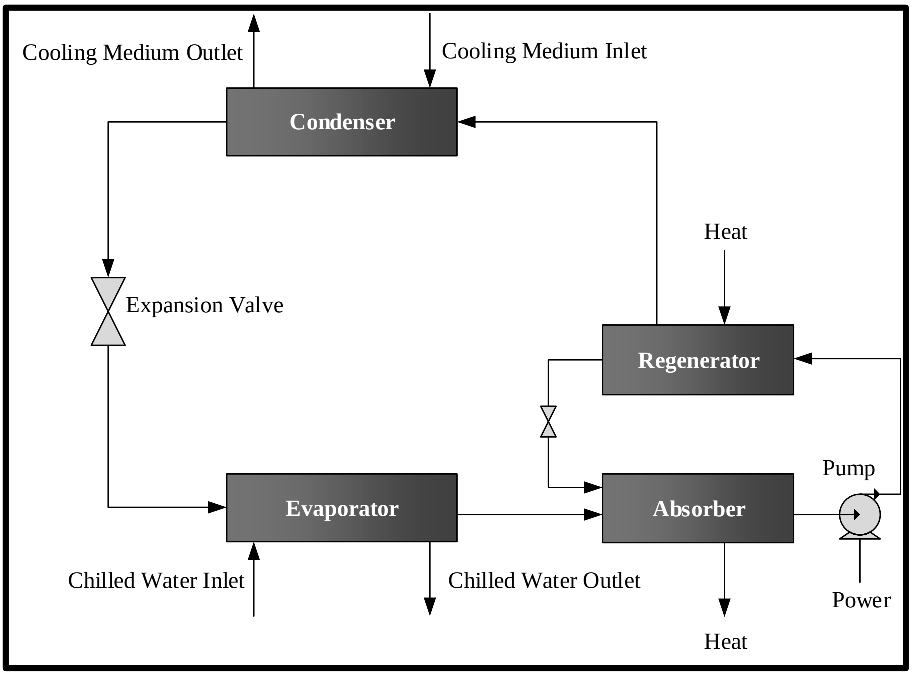

Figure 2.3: Absorption Cycle

(Chartered Institution of Building Services Engineers, 2012)

Conventionally, industrial processes fulfil their energy requirements by purchasing power from centralised power plants and by producing heat on-site through combustion of fossil fuel (Figure 2.4) (Beith, 2011). These systems have excellent economies of scale, but usually transmit power to long distances resulting in sizable losses. In addition, power plants emit a certain amount of heat during power generation which is then released into the environment via cooling towers, flue gases and by other means. Large power plants can only use co-generation or tri-generation systems only when sufficient need exists in immediate geographic vicinity for an industrial complex, additional power plant or a city. In the past decade however, decentralised energy systems have attained significant development in energy production (Jradi and Riffat, 2014; Liu et al., 2014a). Decentralised energy systems are defined as energy systems located in or near user facilities to meet local user demands in top priority (Wu and Wang, 2006).

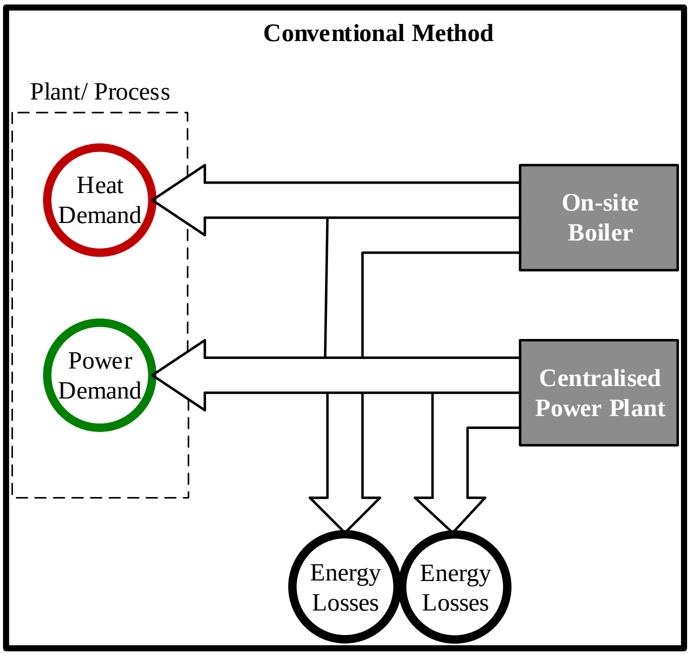

Figure 2.4: Conventional Method of Heat and Power Generation (Combined Heat and Power Association, 2014)

Decentralised energy systems possess several advantages over the conventional centralised energy system. The first advantage is its overall energy conversion efficiency. According to literature (Al-Sulaiman et al., 2011; Stojkov et al., 2011; Wu and Wang, 2006), the overall energy conversion efficiency in decentralised energy systems is significantly improved, ranging between 70 to 90% as compared with 30 to 45% of typical centralised power plants. This means that less fuel is required for decentralised energy systems to obtain the same amount of heat and power compared to conventional modes.

The second advantage of decentralised energy systems is emission reduction (Majutek Perunding, 2014; Stojkov et al., 2011). By installing energy systems on-site, would reduce the dependency on large centralised power plants which excessively utilise fossil fuel to supply power and hence, reducing greenhouse gas (GHG) emissions (Wu and Wang, 2006). Such emissions can be further reduced, if decentralised energy systems use a more sustainable source of fuel such as biomass instead of fossil fuel (Abdullah and Sulaiman, 2013; Zafar, 2014). This can be beneficial to industries that produce high amounts of biomass as waste products, as implementing a decentralised energy system can reduce or eliminate disposal problems (Abdullah and Sulaiman, 2013).

Another advantage of using decentralised energy systems is the distance to the end user. There is no need to transport the power over long distances and face transmission losses (Beith, 2011). This also means that power requirements on centralised power plants can be reduced, resulting in less investment costs for upgrades. This is evident as a 2011 report from Climate Works titled “Unlocking Barriers to Cogeneration” stated that billions of dollars on upgrading and maintaining the national grid in Australia can be saved with the widespread use of on-site energy systems (Climate Works Australia, 2011).

Lastly, decentralised energy systems increase the reliability of the energy supply network (Wu and Wang, 2006). Since centralised power plants may experience disruptions in energy supply due to various reasons (e.g., malfunction, sudden shutdown, etc.), decentralised energy systems can potentially reduce the dependence on centralised energy systems and increase reliability of energy production for the grid (Sonar et al., 2013).

However, it is important to note that the aforementioned advantages may not be achieved unless systematic design approaches or frameworks are made available. In this respect, the field of Process Systems Engineering (PSE) has a long standing history in developing systematic approaches to synthesise energy systems. The following sections provide a review of PSE approaches and their application in the synthesis of energy systems.

2.3 Process Systems Engineering (PSE)

Process Systems Engineering (PSE) is a field concerning the development of systematic approaches and tools to perform process synthesis (Sargent, 2005;

Stephanopoulos and Reklaitis, 2011). Process synthesis is defined as "*an act of determining the optimal interconnection of processing units as well as the optimal type and design of the units within a process system*" (Nishida et al., 1981). As stated in its definition, process synthesis requires designers to find an optimum chemical process design that fulfils several aspects such as efficiency, sustainability, economics and etc. (Dimian et al., 2014; El-Halwagi, 2007). In this respect, several systematic approaches have been developed to provide designers a methodological framework for designing chemical processes (Biegler et al., 1997; Douglas, 1988; El-Halwagi, 2007; Seider et al., 2004; Smith, 2005; Stephanopoulos and Reklaitis, 2011). Specifically, these approaches provide guidance in identifying the feasibility of a process before the actual design of its units. Prior to this, several alternatives are generated and evaluated based on design decisions and constraints. After ranking by certain performance criteria, the most convenient alternatives are refined and optimised. By applying these systematic approaches, quasi-optimal targets for process units can be set well ahead of their detailed sizing (Dimian et al., 2014).

Systematic approaches developed in PSE are not just limited to process synthesis. As shown in reviews presented by Barnicki and Siirola (2004), Cecelja et al. (2011), Grossmann and Daichendt (1996), Li and Kraslawski (2004) and Westerberg (2004), systematic approaches have also been developed for the synthesis of energy systems. These approaches are typically categorised into;

1. Heuristic approaches
2. Insight-based approaches
3. Mathematical optimisation approaches

Heuristic approaches use rules derived from engineering knowledge and experience to generate a good base case design (Stephanopoulos and Han, 1996). Subsequently, modifications are performed to the base case to improve its performance (Stephanopoulos and Westerberg, 1976). However, heuristic approaches are often depend on the experience of the designer. Hence, in the case where newly or not established processes are considered, heuristic approaches may not be applicable. In addition, such approach also does not guarantee the optimal configuration for an energy system as heuristics may overlook complex design decisions (Frangopoulos et al., 2002).

Besides heuristics, insight-based approaches have been used to design energy systems. Insight-based approaches combine principles from thermodynamics and other physical sciences to obtain targets for an energy system. A prominent representative of insight-based approaches is Pinch Analysis (Linnhoff et al., 1982; Shang and Kokossis, 2005; Wicks, 1994), which is introduced to integrate a process (via heat exchanger network design) and, identify its heating and cooling requirements (Strouvalis et al., 1998). Pinch Analysis has proven to be very effective in application and provides great energy savings (Kemp, 2007). Other commonly accepted extensions of Pinch Analysis include Total Sites analysis (Dhole and Linnhoff, 1993) and exergy analysis (Sorin et al., 2000). Total Sites analysis (TSA) incorporates several processes serviced by and linked through a central energy system. TSA uses graphical representation of process utilities that enable designers to obtain targets for fuel, co-generation, cooling and etc. (Dhole and Linnhoff, 1993). Exergy analysis gives information on the flow of useful energy through various steps in a process (Sorin et al., 2000). Nevertheless, it is important to realise that insight-based approaches are often used as tools prior to the actual design procedure itself. In particular, these approaches determine utility requirements (of a process) which an energy system should deliver but not explicitly used to screen alternative technologies. On the other hand, insight-based approaches are suitable if the objective is a physical target, such as minimising energy consumption. If the objective is economic in nature (e.g., minimising total costs), insight-based approaches may not be very appropriate (Sanaei and Nakata, 2012). Despite this, some contributions have introduced economics at a secondary level, but it is mathematically non-rigorous and the capital cost of the resulting energy system may be too high (Frangopoulos et al., 2002; Sanaei and Nakata, 2012).

Another category of approaches used to design energy systems are mathematical optimisation approaches. Mathematical optimisation approaches first systematically enumerate several possible unit operations and their alternative system configurations, process integration, operating modes and other important matters in a superstructure representation of an energy system (Liu et al., 2011; Westerberg, 1991; Yeomans and Grossmann, 1999). The behaviour and performance of these alternatives are then mathematically modelled and optimised by searching for the solution that minimises (or maximises) the *objective function* or the optimisation criterion (Floudas, 1995). The outcome or solution of the optimisation would represent the optimal configuration of the energy system. Since mathematical optimisation considers possible alternatives to synthesise an energy system, it is a more comprehensive approach as compared to heuristic approaches and explicitly determines the topology of energy systems unlike insight-based approaches.

In the past, different mathematical optimisation approaches have been vastly and successfully applied in the synthesis of energy systems such as co-generation and tri-generation systems (Yılmaz and Selim, 2013). Section 2.4 discusses further on mathematical optimisation.

2.4 Mathematical Optimisation for Synthesis of Energy Systems

As mentioned in Section 2.3, mathematical optimisation has been used to develop systematic approaches to synthesise energy systems. In general, applied mathematical optimisation approaches consist of the following six steps (Biegler et al., 1997; Hendry et al., 1973);

1. Several possible process unit operations are enumerated.

2. Necessary simplifying assumptions are acknowledged, to suitably reduce the complexity of the process.

3. A superstructure connecting all individual unit operations in all possible ways is developed, according to simplifying assumptions.

4. Behaviour and performance of all unit operations considered in superstructure are mathematically modelled (e.g., including the components, mass and enthalpy flows, together with feedstocks, investments in buildings and equipment, and operations, etc.). Mathematical models range from the relatively straight-forward linear programming (LP) to increasingly complex

mixed-integer linear programming (MILP), non-linear programming (NLP) and mixed-integer non-linear programming (MINLP), which depict real life scenarios more accurately (Grossmann, 2002).

5. An optimisation objective is defined, together with all constraints of the variables.

6. Using an appropriate optimisation approach or algorithm, the optimum selection of equipment and conditions is undertaken.

It is important to note that mathematical optimisation models are developed depending on the nature of the energy system synthesis problem (e.g., single-objective optimisation, multi-objective optimisation, optimisation under uncertainty) (Barnicki and Siirola, 2004; Grossmann and Daichendt, 1996; Grossmann and Guillén-Gosálbez, 2010a; Li and Kraslawski, 2004). Based on the nature of the problem, appropriate approaches and algorithms are used to solve the developed mathematical model. This is further discussed in Sections 2.4.1 - 2.4.3.

2.4.1 Single-objective Optimisation

In a mathematical optimisation model, there can be a number of *equality* and *inequality constraints*. These constraints define the relationship between the decision variables, whose values are determined by optimising (e.g., minimising or maximising) the model according to a specific objective function (Baños et al., 2011;

Edgar et al., 2001; Floudas, 1995). If the objective function is exclusively formulated for a single criterion (e.g., economic performance), it is typically considered as single-objective optimisation (SOO) (Savic, 2002). A basic SOO problem is formulated as shown;

$$\min \quad f(x), \qquad \text{Objective function} \tag{2.1}$$

$$\text{subject to} \quad h(x) = 0, \qquad \text{Equality constraints} \tag{2.2}$$

$$g(x) \leq 0 \qquad \text{Inequality constraints} \tag{2.3}$$

f is the optimisation objective function to be minimised (or maximised) while x is the vector of decision variables (e.g., equipment sizes, types, etc.). Meanwhile h and g are vector functions of the variables x describing the equality (e.g., energy demand) and inequality (e.g., technical, operational limits of equipment, performance targets) constraints respectively (Edgar et al., 2001). To solve SOO problems, there are several algorithms available depending on the mathematical nature of the optimisation model (e.g., LP, MILP, NLP and MINLP). These algorithms can be distinguished as traditional optimisation and meta-heuristic optimisation.

Traditional optimisation algorithms follows a pre-determined solution search pattern. These search patterns differ based on the mathematical nature of the optimisation problem. In LP problems, the optimal solution always lies on the boundary of the feasible region defined by specified constraints (Figure 2.5(a)). To seek this optimal solution, the simplex algorithm was developed by George B. Dantzig in 1947. The simplex algorithm seeks the optimal solution by following the edges of the feasible region until it reaches the vertex with the optimal objective function value (Figure 2.5(b)). This optimal objective function value is guaranteed to be the global optimal solution as LP problems are by definition convex. An optimisation problem is convex when there is only one global optimal solution and no local optimal solutions.

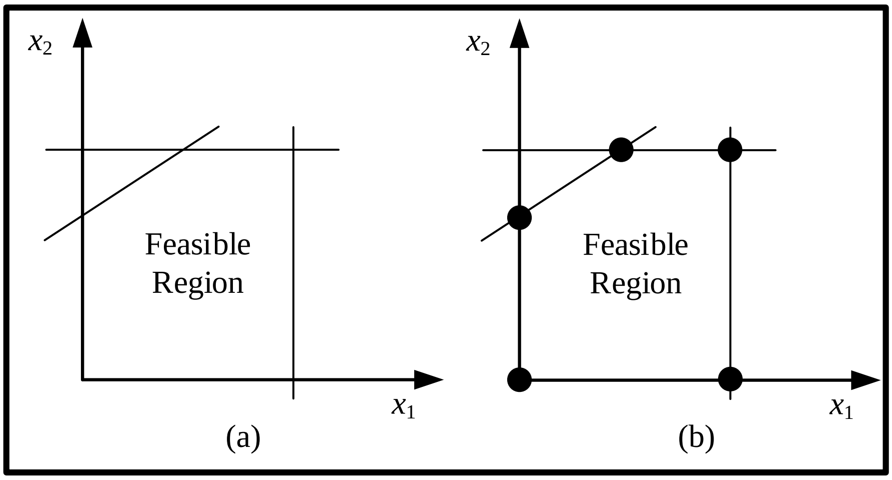

Figure 2.5: (a) Feasible Region for LP Optimisation Problems, (b) Solutions for LP Optimisation Problems

For NLP problems, the optimal solution is generally not found on the boundary, but within the feasible region. To seek for the optimal solution in NLP, gradient-based methods are used. The gradient-based method employs derivatives of the objective function to search for optimal solutions. The first derivative, *f'(x)* represents the rate of change of a function, *f(x)*. In order to find the optimal solution, *f'(x)* must be equal to zero (Figure 2.6(a)). Some gradient-based methods go further to the second derivative *f''(x)*. *f''(x)* represents the rate of change of the first derivative. If the sign of *f''(x)* is negative, the gradient of the first derivative is decreasing, making it a maximum point. However, NLP algorithms often have non-convex feasible regions. As shown in Figure 2.6(b), an optimisation problem is non-convex when there are several local optimal solutions existing. As such, gradient-based methods generally require good initial solutions to achieve convergence (Tawarmalani and Sahinidis, 2002). Otherwise, search algorithm can get stuck in local optimal solutions. In addition, the identified optimal solution may not necessarily be the global optimal solution, thus, gradient-based methods cannot guarantee global optimality.

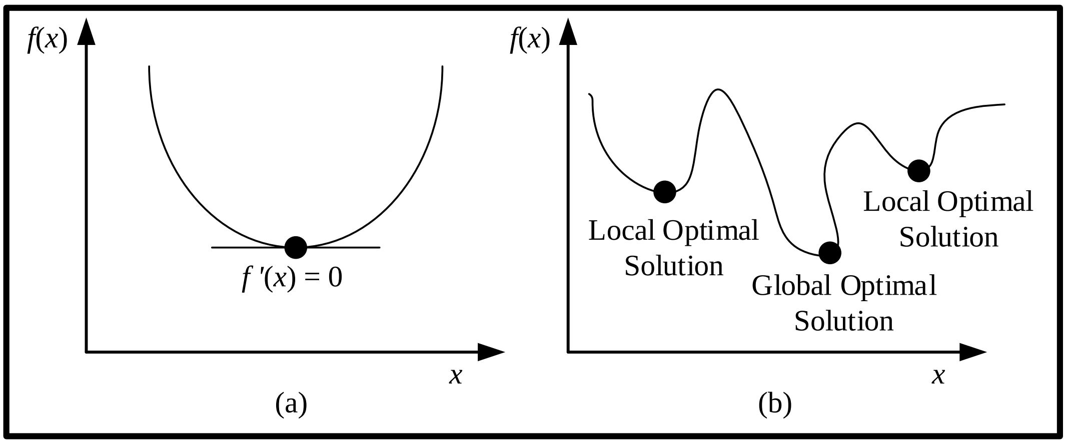

Figure 2.6: (a) Optimal Solution for NLP Problems, (b) Local and Global Optimal Solutions for Non-Convex NLP Problems

On the other hand, MILP problems are solved via the branch-and-bound algorithm developed by Land and Doig (1960). The branch-and-bound algorithm systematically details a subset of candidate solutions while removing a large number of unqualified solutions. This is achieved by branching the overall problem repeatedly into a set of sub-problems. The branch-and-bound algorithm will then decide which sub-problems can be excluded or require further branching. In this way, the problem can be solved to global optimality. Meanwhile, MINLP problems are solved using global optimisation algorithms (Horst and Tuy, 1996). This algorithm uses branch-and-bound like techniques to decompose large and complex MINLP problems into a set of smaller sub-problems (Misener et al., 2009; Tawarmalani and Sahinidis, 2004). These sub-problems are then further analysed to either show no feasible or optimal solutions or to identify the global optimal solutions to the sub-problems, or further decompose the sub-problems for further analysis. In theory, such strategy is expected to determine the global optimal solution for non-linear problems. However, for real-world problems, global optimisation algorithms are mostly still not capable of identifying the global optimal solution within acceptable computation times for engineering practice (Rebennack et al., 2011).

Unlike traditional optimisation, meta-heuristic optimisation algorithms use randomised search algorithms to thoroughly explore the search space. To search for the optimal solution, these algorithms iteratively try to improve a candidate solution. As such, they can be applied to problems of which the mathematical formulation is not known (black-box models), the calculation of derivatives is excessively complex, or when traditional algorithms fail. If such algorithms are executed with a sound strategy, they would not get stuck in local optimal solutions. A typical meta-heuristic optimisation algorithm applied in the synthesis of energy systems include evolutionary algorithms (EAs) (Baños et al., 2011; Černý, 1985; Kirkpatrick, 1984).

EAs form a subset of meta-heuristic optimisation which is inspired by biological evolution (Eiben and Smith, 2003). EAs are derivative-free algorithms for numerical optimisation of (non-)linear, (non-)convex mixed-integer optimisation problems. As shown in Figure 2.7, EAs are iterative loops which start with a one-time initialisation and evaluation step, whereby a set (*population*) of candidate solutions (*individuals*) is randomly created and evaluated using an objective function (*fitness function*). Based on fitness function values, parent individuals are selected to create new individuals by *mating selection*. New individuals are created by performing *recombination* and *mutation*. Recombination randomly takes and reassembles parts from the selected parents to create a new offspring. Mutation then randomly alters single parent individuals to create new individuals. The newly created offspring is then *evaluated*. This is followed by environmental selection, where individuals from the population that will least likely evolve into the optimal solution would be eliminated. The described loop continues this evolution process until a termination criterion is achieved (e.g., maximum number of generations, or maximum number of generations without improvement of objective function). During this entire process, EAs generate a range of solutions rather than only a single optimal solution. Although convergence towards the global optimal solution can generally not be guaranteed for a limited number of objective function evaluations, EAs are still regarded as global optimisation. Moreover, a well-designed EA will usually not get stuck in local optimal solutions, but will find optimal or near-optimal solutions. A prominent implementation of EAs can be seen in genetic algorithms (GAs) (Pezzini et al., 2011). Despite being considered as global optimisation, meta-heuristic algorithms generally have very slow convergence and must usually be tuned to a particular problem. Besides, the solution obtained from the algorithms is not necessarily the global solution, but a near approximation of it.

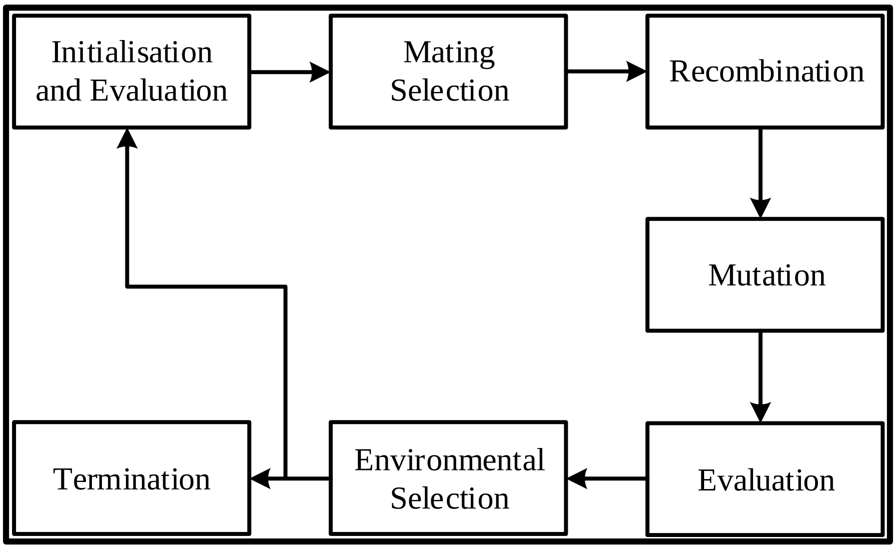

Figure 2.7: Procedure for Evolutionary Algorithms

Despite having several algorithms for SOO, it is insufficient to optimise a single-objective criterion as real-world synthesis problems often consider multiple conflicting objectives such as economic, environmental and social aspects (Grossmann and Guillén-Gosálbez, 2010a, 2010b; Li and Kraslawski, 2004). Hence, by considering only a single-objective in process optimisation, it may introduce undesired preferences for other objectives into the optimisation. To address this issue, multi-objective optimisation (MOO) approaches have been developed (Osyczka, 1981). The concept of MOO and its application in the synthesis of energy systems is discussed in Section 2.4.2.

2.4.2 Multi-objective Optimisation

As opposed to SOO in Section 2.4.1, MOO is used to simultaneously optimise a problem according to two or more conflicting objectives. It is a method suitable for problems which require a trade-off among its considered objectives. A basic MOO problem with k objective functions can be formulated as shown;

$$\min \quad (f_1(x), f_2(x),..., f_k(x))^T \tag{2.4}$$

$$\text{subject to} \quad x \in \Omega, \tag{2.5}$$

$$h(x) = 0, \tag{2.6}$$

$$g(x) \leq 0 \tag{2.7}$$

The vector of objective functions is denoted by $f(x) = (f_1(x), f_2(x),..., f_k(x))^T$. The decision variable vector $x = (x_1, x_2,.., x_k)^T$ belongs to the feasible region Ω.

MOO problems with conflicting objectives do not have a single solution, but a set of optimal solutions. In this respect, the multi-dimensional concept of "dominance" is used to decide if one solution is better than other solutions (Deb, 2001). A solution a is said to dominate a solution b if the following two are true;

1. a is no worse than b in all objectives
2. a is better than b in at least one objective

The solution to MOO problems is the set of non-dominated solutions, otherwise known as the Pareto set. A solution belongs to the Pareto set if no improvement is possible in one objective without losing in other objectives. This concept is illustrated in Figure 2.8.

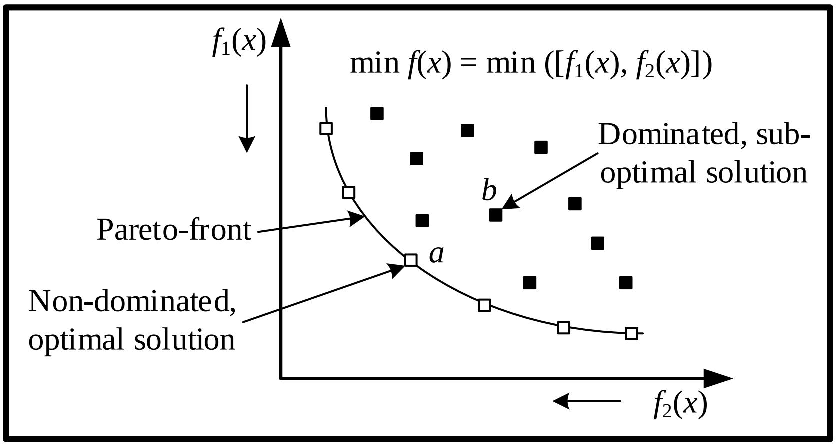

Figure 2.8: Pareto-front for Two-objective Problem

To find a single solution for a MOO problem however, it would require two stages; optimisation and decision making (Deb, 2001). Depending on the order in which these stages are performed, there are two classes of approaches used to obtain a single solution for a MOO problem (Figure 2.9). As shown in Figure 2.9 (left-hand side), the first class of approaches is the *a priori* approaches, which require information on the decision maker's preference before the solution process starts. These approaches essentially transform the MOO problem into a SOO problem. An example of such approaches would be the weighted sum. The second class of approaches (right-hand side of Figure 2.9) would be the *a posteriori* approaches, which generate Pareto-optimal solutions to approximate the Pareto set. The decision maker then analyses the generated solutions to choose the one with the preferred trade-offs. Commonly used *a posteriori* approaches include (but not limited to) ε-constraint (Chankong and Haimes, 1983; Haimes et al., 1971), fuzzy optimisation (Bellman and Zadeh, 1970; Zimmermann, 1978) and evolutionary multi-objective algorithms (EMOAs).

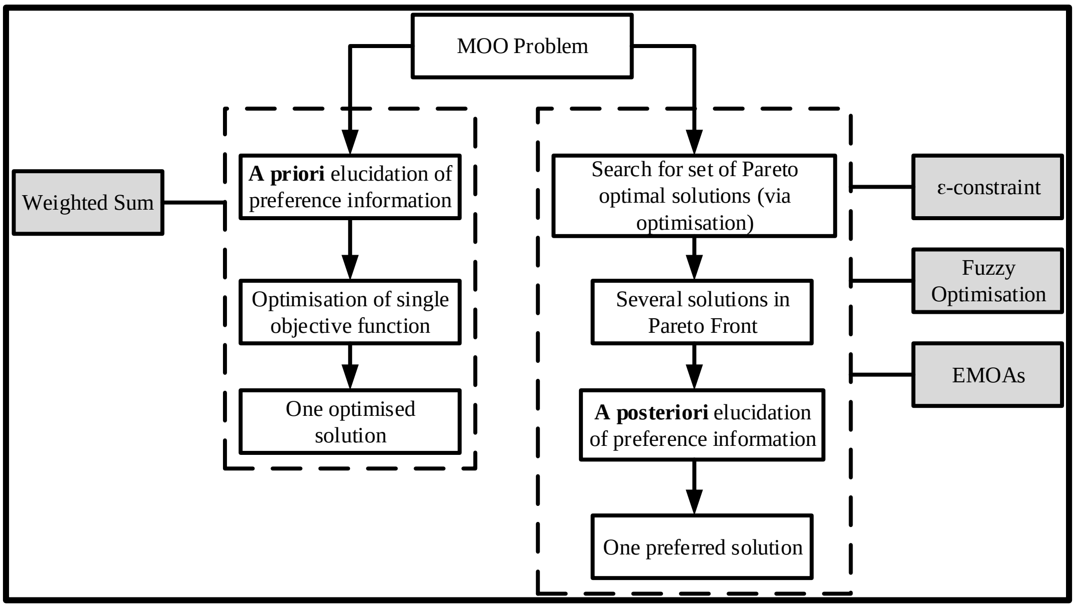

Figure 2.9: Approaches for MOO problems

In weighted sum, multiple objective functions are transformed into a single-objective function by weighting each objective and optimising the weighted sum of the objectives. The weighting coefficient of each objective must be specified before optimisation. This would mean that the decision maker would require prior knowledge when specifying these weighting coefficients. Despite its simplicity in application, the weighted sum approach requires the considered objectives to be quantified uniformly. For instance, if economic performance and environmental impact are considered as the objectives, then both objectives must be quantified with the same units. Otherwise, the solution obtained from this approach may not represent an accurate trade-off between the considered objectives.

On the other hand, the ε-constraint was proposed by Haimes et al. (1971). It is an approach which converts the MOO problem into a set of SOO problems. The problem is optimised with respect to one of the multiple objective functions while upper and lower bounds are set for all other objective functions (Dua and Pistikopoulos, 1999). Once the problem is optimised, the bounds are systematically changed to approximate the Pareto set (Voll, 2014). The Pareto set represents all the reasonable actions a rational decision maker can take. Based on the Pareto set, the generated solutions are analysed and the preferred trade-off between objectives is chosen.

Besides ε-constraint, fuzzy optimisation has been used to address MOO problems. In fuzzy optimisation, multiple conflicting objectives are integrated into a single continuous interdependence variable λ known as the degree of satisfaction (Bellman and Zadeh, 1970). This achieved by normalising each solution of an objective between 0 and 1 (0 being the worst performance/satisfaction of an objective while 1 being the best performance/satisfaction) (Tan et al., 2011, 2009). With λ representing the interaction between several considered objectives, λ is maximised subject to pre-set upper and lower bounds in order to obtain the highest satisfaction of each objective. In this respect, only the partial satisfaction of the objectives may be achieved, resulting to a compromised solution among all considered objectives. This can be understood as a max-min aggregation rule, where the maximum distance to the goal (e.g., the worse performance of an objective) is minimised (Zimmermann, 1978).

From a meta-heuristic standpoint, EMOAs are population-based procedures used to solve MOO problems (Zitzler and Thiele, 1998). EMOAs can be classified into criterion selection techniques and aggregation selection techniques. Schaffer

(1985) proposed a criterion selection technique that is generally considered the first implementation of an EMOA. The basic concept of this technique is to generate *k* sub-populations for each of the *k* objectives to be optimised. Each sub-population is optimised with respect to one of the *k* objective functions. For mating selection, the sub-populations are shuffled and re-partitioned. Finally, recombination, mutation, and environmental selection are applied to the new population as for a standard single-objective EA. Besides the criterion selection technique, Hajela and Lin (1992) and Ishibuchi and Murata (1998) proposed aggregation selection EMOAs that employ the weighting method. Instead than using constant weights for the objective functions like in the weighted sum method, the weights are varied during optimisation; from generation to generation and/or from function evaluation to function evaluation. Depending on the specific implementation, the weights are assigned randomly or according to heuristic strategy.

In general, *a priori* approaches can be very useful when detailed preference information is known beforehand. Moreover, approaches such as the weighted sum method are usually not labour or computationally intensive as they are easy to program and apply. In spite of this, it is difficult to determine the appropriate value of weights in most cases because solutions obtained are sensitive to the set of parameters considered. This means that inconsistencies in any specified weight would lead to a biased result. On the other hand, such method is only effective if the conflicting objectives can be described by the same measurement (e.g., environmental impact measured in terms of penalty costs for an economic objective function). As such, *a posteriori* approaches are found to be more methodical, practical and less subjective or biased as compared to *a priori* approaches. This is evident as *a posteriori* approaches provide a wider range of alternatives to choose from and conserving information that would have been lost using other approaches. Following this, decision makers are able to make more informed decisions. However, there are several drawbacks found in use of *a posteriori* approaches. For instance, solutions obtained from EMOAs are very much dependent on how well is the search procedure is designed. Even if executed properly, EMOA solutions are not necessarily guaranteed as the global solution. Apart from that, EMOAs and the ε-constraint method tend to be time consuming due to its large computational nature. Although fuzzy optimisation may be computationally favourable, is it most suited for MOO problems there are linear due to its underlying assumption of linear membership between considered objectives.

Despite the usefulness of MOO approaches, it has been widely applied in deterministic environments where solutions may be discrete values for a single operating scenario. However, such solution may not necessarily be feasible in real world applications where uncertainties are present. Uncertainties are uncertain events which may cause disturbances on energy systems operations. In this respect, Section 2.4.3 discusses optimisation approaches used to account for uncertainties in the synthesis of energy systems.

2.4.3 Optimisation under Uncertainty

As mentioned at the end of Section 2.4.2, uncertainties have a significant impact in energy systems synthesis problems. Uncertainty is the lack of knowledge of how the future will unfold (Grossmann and Sargent, 1978; Hastings and McManus, 2004). The sources of uncertainties can be categorised into short-term and long-term uncertainties (Subrahmanyam et al., 1994). Short-term uncertainties mainly include operational variations, equipment failure and sudden shutdown. Long-term uncertainties refer to supply and demand variations, and price fluctuations (Shah, 1998). Such uncertain events are certainly unavoidable and would cause a large disturbance toward energy systems operations, leading to a sub-optimal design (Liu et al., 2013, 2011). In this respect, optimisation under uncertainty makes it possible to account for the impacts of uncertainties on an energy system at the design or synthesis stage. Several approaches have been suggested to address such uncertainties in a systematic manner. These approaches typically differ in the way the uncertain variables are handled or represented during optimisation (Figure 2.10). As shown in Figure 2.10, approaches for optimisation under uncertainty can be divided into two categories; continuous and discrete distribution.

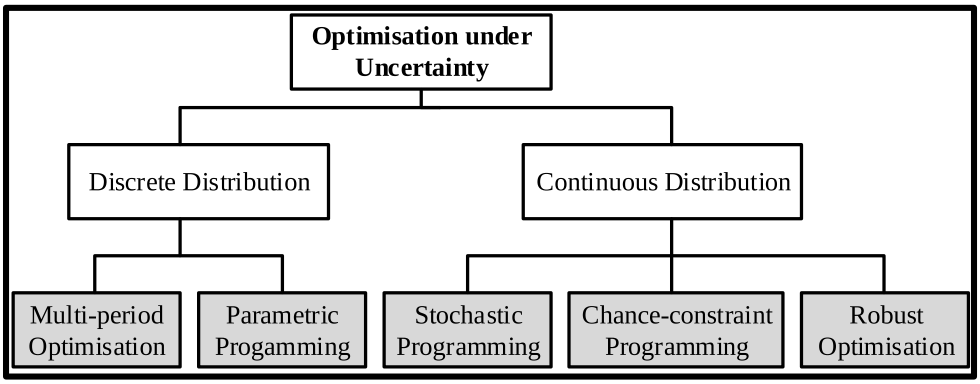

Figure 2.10: Approaches for Optimisation under Uncertainty

Continuous distribution approaches consider continuous stochastic distribution of the uncertain variables. Typical continuous distribution approaches used for solving energy synthesis problems with uncertainties include (but not limited to) stochastic programming (e.g., Liu, 2009), chance-constrained programming (e.g., Cai et al., 2009) and robust optimisation (e.g., Kasivisvanathan et al., 2014).

In stochastic programming, mathematical models are defined with a set of uncertain parameters (e.g., energy demand, raw material supply, etc.) which are normally described by continuous distributions. This would give rise to scenarios that correspond to a particular realisation of each uncertain parameter (Grossmann and Guillén-Gosálbez, 2010a; Vanek et al., 2012). The fundamental idea behind stochastic programming is the concept of recourse. Recourse is the ability to take corrective action after realisation of scenario has taken place (Sahinidis, 2004). In its general form, stochastic programming with recourse is presented as a two-stage programming problem (Dantzig, 1955; Grossmann and Guillén-Gosálbez, 2010b). In the first stage, decision variables are pre-determined before the realisation of the uncertain variables. In the second stage, a finite number of uncertain parameters scenarios are generated. In this stage, violation of the constraints is allowed, but penalised through penalty terms in the objective function. This penalty also known as a recourse variable, leads to additional costs being indexed by scenario. This would mean that every possible parameter realisation has an associated recourse action. This approach is suitable when the objective function and constraint violations can be described by the same measurement. However, the drawback of this approach is the prohibitive growth in the model size as the number of considered scenarios increases (Liu, 2009). Alternatively, the expectation of the recourse objective function term is determined through the integration of the given multivariate probability distribution function. In this way, the problem size is much smaller but the formulation becomes non-linear. In order to remove the non-linearity, techniques such as Monte Carlo, Gaussian quadrature, etc. are used (Verderame et al., 2010). However, these techniques may become computationally expensive as the number of uncertain parameters increase.

On the other hand, a viable alternative to stochastic programming is chance-constrained programming (CCP) (Charnes and Cooper, 1963, 1962, 1959). In CCP, the focus is on the reliability of the system, i.e., the system's ability to meet feasibility in an uncertain environment. This reliability is expressed as a minimum requirement on the probability of satisfying constraints (Sahinidis, 2004). Thus, the objective function is expressed in terms of expected value, while the constraints are expressed in terms of fractiles, i.e., the point below a stated fraction (or decimal equivalence) of the values (as shown below).

$$\max \quad c^t(x), \tag{2.8}$$

$$\text{subject to} \quad P(Ax \geq b) \geq p, \tag{2.9}$$

$$x \geq 0 \tag{2.10}$$

As shown, c and x are n-vectors, b is an m-vector while A is an $m \times n$ matrix. It is assumed that there is an uncertainty for constraint matrix A and b, and that the system is required to satisfy the corresponding constraint with a probability $p \in (0,1)$ (Sahinidis, 2004). The constraints containing uncertain parameters are now replaced with their respective probabilistic forms which explicitly take into account the stochastic nature of the uncertain parameters. CCP is useful to deal with inequality constraints where it is highly desirable to satisfy, but not absolutely essential

(Grossmann and Guillén-Gosálbez, 2010a). However, this approach cannot guarantee the feasibility of a given solution with regard to the specific realisation of uncertain parameters. In order to address this issue, robust optimisation approaches have been developed.

Robust optimisation, which was first introduced by Ben-Tal and Nemirovski (1998), seeks to determine a robust feasible solution to an uncertain problem (Bertsimas et al., 2010; Mulvey et al., 1995). This means that the solution obtained should be guaranteed to remain feasible in the range of the uncertainty set considered for a pre-defined probability level. The difference between robust optimisation and stochastic programming with recourse is the explicit consideration of feasibility issues. In robust optimisation, the solution must ensure that a set of constraints will be satisfied with a certain probability when the uncertainty is realised. Meanwhile, stochastic programming either assumes complete recourse, i.e., every scenario is supposed to be feasible, or allows infeasibilities at a certain penalty (Grossmann and Guillén-Gosálbez, 2010a). Furthermore, robust optimisation cannot handle recourse variables. More importantly, robust optimisation translates and simplifies uncertainties into deterministic values, making it a suited approach for small time frame problems. Because of this simplification, robust optimisation usually leads to lower computational requirements. However, the difficulty in solving these problems still lies in the computation of the probability and its derivatives of satisfying inequality constraints. In addition, robust optimisation assumes limited information about the distributions of the uncertainties, such as the mean value and its range (Leiras et al., 2010). Although it has low computational intensity, robust optimisation accepts a sub-optimal solution to ensure that, when the data changes, the solution remains feasible and near optimal.

Besides continuous distribution approaches, discrete distribution approaches have also been used to account for uncertainties in energy systems synthesis. In discrete distribution approaches, the bounded uncertain variables are discretised into multiple intervals such that each individual interval represents a scenario with an approximated discrete distribution. Examples of the discrete distribution approaches used to solve energy synthesis problems with uncertainties include parametric programming (e.g., Papalexandri and Dimkou, 1998) and multi-period optimisation (e.g., Iyer and Grossmann, 1998).

Parametric programming is an approach based on the theory of sensitivity analysis. It aims to define a function that relates the uncertain parameter values to a given optimal solution for the entire parameter space (Dua and Pistikopoulos, 1999; Papalexandri and Dimkou, 1998; Romanko et al., 2012). However, it should be noted that parametric programming requires solving a series of optimisation problems in an iterative manner, making it computationally intensive (Verderame et al., 2010). With such high computational time required, application of parametric programming may be very challenging for large-scale industrial problems.

Lastly, multi-period optimisation is an approach that provides a unique solution that is feasible for a given set of anticipated scenarios (Grossmann and Sargent, 1978; Hui and Natori, 1996). In this approach, the bounded uncertain variables are discretised into multiple intervals such that each individual interval represents a scenario with an approximated discrete distribution (Halemane and Grossmann, 1983; Pistikopoulos and Ierapetritou, 1995; Rooney and Biegler, 1999; Subrahmanyam et al., 1994). The solution obtained is desirable as its feasibility is assessed for all potential scenarios considered.

From the reviews in Sections 2.4.1 – 2.4.3, it is clear there are several mathematical optimisation approaches available to synthesise of energy systems. Section 2.5 discusses the mathematical optimisation approaches applied in the past to synthesise of energy systems.

2.5 Synthesis of Energy Systems

The previous approaches presented in the literature with respect to the synthesis of energy systems can be categorised into hierarchical approaches and integrated approaches. Section 2.5.1 reviews the hierarchical approaches developed for synthesising energy systems.

2.5.1 Hierarchical Approaches

According to Frangopoulos et al. (2002), hierarchical approach for synthesis of energy systems can be divided into the following three levels;

1. Synthesis optimisation
2. Design optimisation
3. Operational optimisation

At the synthesis level, optimisation is performed to establish the configuration of the energy system. This would consist of the selection of the technological components and the optimal layout of their connections. At the design level, technical specifications (e.g. capacity, operating limits, etc.) are to be defined for the units selected during synthesis. Lastly, the optimal operation mode (e.g. temperatures, pressures flow rates, uncertainties etc.) is to be defined in the operational level given that the system synthesis and design is provided. This is summarised in Figure 2.11.

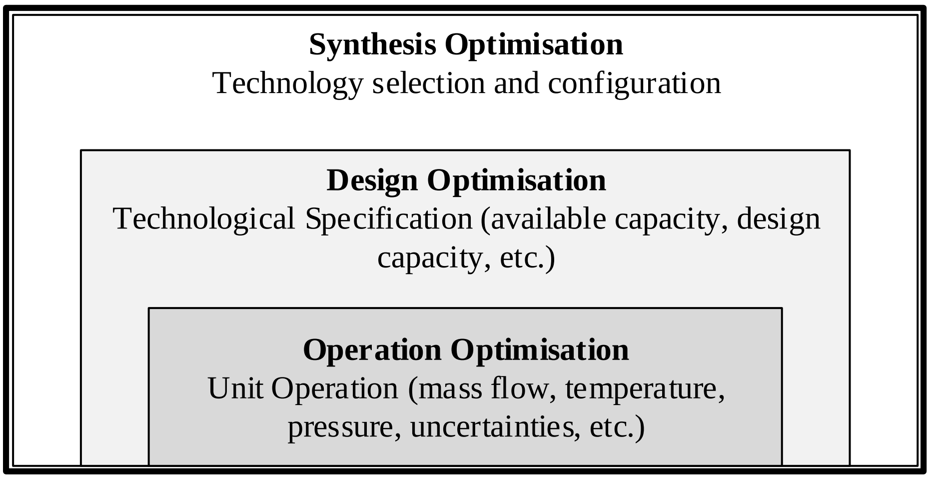

Figure 2.11: Levels of Synthesis for Energy Systems (Frangopoulos, 2003)

As shown in literature, several research works have been performed with respect to the synthesis and design optimisation levels. For instance, Papaulias and Grossmann (1983) presented one of the earliest superstructure based approaches to synthesise a co-generation system which is required to provide fixed demands of power for drivers and steam at various at levels. Chang and Hwang (1996) presented a MOO approach to synthesise an energy system with minimum waste taking into account economic incentives and environmental penalties. Next, Maréchal and Kalitventzeff (1998) proposed a three step superstructure based approach to synthesise an optimal co-generation system. In the first step, a generic co-generation superstructure was used to identify the technologies required for meeting process energy requirements. Using the results from the first step, the second step selects the available technologies that fit such requirements. The third step targets the optimal process configuration. Meanwhile, Lozano et al. (2009) proposed an approach to determine optimal configuration of a tri-generation system installed in the tertiary sector based on a superstructure that considered the type, number and capacity of equipment. Later, Lozano et al. (2010) extended the previous work by introducing a cost optimisation approach for the design of a tri-generation system. Later, Carvalho et al. (2011) developed a model to determine the optimal configuration from a tri-generation superstructure to meet specific demands of a hospital subject to environmental constraints such as kilograms of CO_2 released and Eco-indicator 99 Single Score. Recently, Yokoyama et al. (2015) developed a hierarchical optimisation approach to determine the types, capacities and number of equipment in consideration of their operational strategies corresponding to seasonal and hourly variations in energy demands for a co-generation system. In the presented approach, the design variables are optimised at the upper level while the values of operation variables are independently optimised at the lower level for each operating period. However, the type, size and configuration of technologies for an energy system cannot be decided without consideration of its operating strategy. Regardless of the application and technologies employed, the operation strategy is the critical factor governing the overall layout and performance of any energy system (Cho et al., 2014; Jradi and Riffat, 2014). With a suitable operating strategy, the energy system is able to reduce its overall fuel consumption and subsequently its operational costs.

Several works have been reported in literature which study different operation strategies for a energy system (Cho et al., 2014; Jradi and Riffat, 2014; Liu et al., 2014a). According to Kavvadias et al. (2010), the two commonly investigated operation strategies in industry are;

- <u>Following Electrical Load (FEL)</u>

  In FEL strategy, an energy system is independent of the power utility from the grid. All site power requirements, including the reserves needed during scheduled and unscheduled maintenance, are taken into account when sizing the system. Such system is also referred to as "stand-alone" system. If the site heat demand is higher than the available heat generated by the energy system, auxiliary boilers are used. Conversely, when site heat demand is low, the heat generated will be released as waste. If there is a possibility, the excess heat can be exported to neighbouring facilities. This strategy is usually implemented when the ratio of heat demand to power demand is low.

- <u>Following Thermal Load (FTL)</u>

  In FTL, an energy system is operated following the heat demand. During the period when the power demand exceeds the generation capacity, the deficit of power can be compensated by power purchased from the grid. Similarly, if the local legislation permits, surplus power produced can be sold to the grid or neighbouring facilities. This strategy is normally implemented when the ratio of heat demand to power demand is high.

Several works have studied FEL and FTL strategies to improve the overall performance of tri-generation systems. For instance, Jalalzadeh-Azar et al. (2004) presented a comparative analysis on FEL and FTL operation strategies for a micro-turbine driven tri-generation system based on energy costs and primary energy consumption (PEC). Meanwhile, Mago et al. (2009) compared FEL and FTL strategies for internal combustion engine-based tri-generation system in four climatic conditions based on their energy consumption, CO_2 emissions and costs. Besides, Smith et al. (2010) performed a detailed analysis on simulation predictions of tri-generation system performance parameters in FEL and FTL operating strategies. Recently, Jing et al. (2012) optimised the operation strategy of a tri-generation system based on life cycle assessment. Although FEL and FTL strategies are commonly implemented in energy system operations, they may not guarantee the best performance of the system.

It is reported that both FEL and FTL operation strategies lead to considerable waste of energy (Chicco and Mancarella, 2008). For instance, when the heat demand is low, FEL strategies generate excess heat that is eventually released as waste energy into the atmosphere since its main priority is to meet power demands. Meanwhile, the FTL strategy may generate excess power which in practice is just wasted if power demands are low. In this respect, several research works proposed a strategy in which an energy system can switch between FEL and FTL based on given energy demands (Liu et al., 2014). Mago and Chamra (2009) presented an optimised hybrid electric–thermal load operation strategy (HETS) to reduce PEC, operating costs and CO_2 emissions compared to conventional operation strategies. In another study, Mago and Hueffed (2010) evaluated the performance of a turbine-driven tri-generation system based on three different operation strategies i.e., FEL, FTL, seasonal strategy and compared them to a reference case. In this work, it was concluded that the seasonal strategy achieved the largest reduction on PEC compared to the reference case. Later, Fang et al. (2012) proposed a switching strategy based on an integrated performance criterion (IPC). The IPC simultaneously considers reduction of PEC, operational costs and carbon dioxide emissions. IPC is used to determine the switching action between FEL and FTL operation strategies. However, the aforementioned contributions focus only on deterministic environments. In deterministic environments, the outcome of optimisation is based on a single operating scenario whereby variations or uncertainties in operations are not considered. In reality, operations within an energy system are susceptible to potential uncertainties.

Uncertainties may arise in various forms such as uncertainty in energy demand and supply, uncertainty in economic parameters (e.g., energy prices) and uncertainty in technological parameters (e.g., availability and reliability of equipment) (Liu et al., 2013). In the event where uncertainties are not taken into consideration, the performance of operations may deviate significantly from the optimal design. In this respect, several studies on operational studies taken uncertainties into account. For instance, Marechal and Kalitventzeff (2003) presented a multi-period targeting approach for energy systems. The proposed multi-period optimisation is used to target utility requirements of an energy system based on varying requirements from a chemical process. Li et al. (2010) proposed a model to optimise a tri-generation system under uncertainty in energy demands using the Monte Carlo method. Lozano et al. (2011) presented a model which analyses the allocation of cost for the operation of a tri-generation system based on uncertainties in energy supply services, fuel prices and energy prices. Meanwhile, Carpaneto et al. (2011a,b) presented a framework which identifies (large and small scale) uncertainties within co-generation operations and selects the best planning solution. Besides, Velasco-Garcia et al. (2011) presented an approach in optimisation-based decision making for an energy system. The approach takes into account the changes in steam demands and costs of associated with starting up and operating units during operations. Rezvan et al. (2013) used stochastic programming and probabilistic theory to determine capacity of a tri-generation system based on uncertainties in energy demand for a hospital in Iran. Mitra et al. (2013) presented a mathematical model to determine the optimal scheduling of industrial co-generation systems under time-dependent electricity prices. More recently, Kopanos and Pistikopoulos (2014) presented a reactive scheduling approach which uses parametric programming to address uncertain scheduling parameters in co-generation operations. Meanwhile, Kasivisvanathan et al. (2014) presented a robust optimisation approach to operate a multi-functional energy system considering uncertainties. The robust optimisation is used to account for uncertainties in feedstock supply and energy/product demand. Similarly, Bischi et al. (2014) presented a detailed optimisation model for planning short-term operation of a tri-generation system. The developed optimisation model determines an operating schedule that minimises the total operating and maintenance costs based on time-varying loads, tariffs and ambient conditions.

Based on the above literature review, it is well documented that several studies focused on operation strategies or operation uncertainties (e.g., supply and demand profiles, fluctuating prices, equipment failure and etc.) without considering its effect on the tri-generation system design. However, some designs may not be sufficiently robust to cope with anticipated uncertainties or changes in operational strategies. This is because operating strategies and corresponding uncertainties have a direct influence on the solution of design and synthesis decisions. Furthermore, designing energy systems based only on steady-state assumptions can lead to systems difficult to operate, exhibit poor dynamic performance and unexpected behaviour under uncertainties. This would induce a need to reconsider key design decisions made initially, resulting in a large amount of rework and extra cost for completion of the design (Herder and Weijnen, 2000).

If the objective is to establish a completely optimised energy system, the three (e.g., synthesis, design and operation) optimisation levels in Figure 2.11 cannot be considered in complete isolation from one another (Frangopoulos et al., 2002; Voll, 2014). In this respect, Herder and Weijnen (2000) and Vega et al. (2014) stress on the need to consider all levels in an integrated manner (shown in Figure 2.12). The integrated approach can produce significant economic benefits and improvement of system operation, as it considers the important relationship of operations in the initial levels of the design procedure.

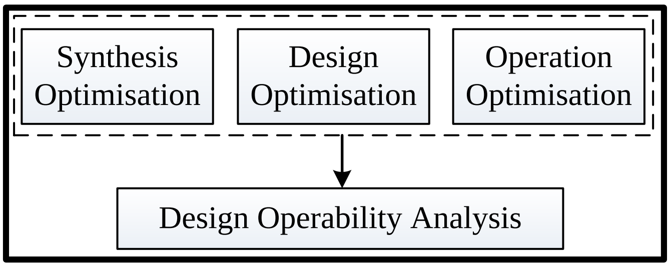

Figure 2.12: Integrated Approach for Synthesis of Energy Systems

2.5.2 Integrated Approaches

As emphasised at the end of Section 2.5.1, the integrated approach relies on the fact that the achievable operational performance of an energy system is a property inherent to synthesis and design optimisation. In this respect, several works have presented integrated approaches for energy systems design. For instance, Hui and Natori (1996) presented a multi-period optimisation approach to synthesise an energy system. With their approach, Hui and Natori (1996) investigated several operational issues which include boiler and maintenance schedules, new equipment selection for debottlenecking and etc. Later, Iyer and Grossmann (1998) developed a multi-period optimisation approach to synthesise and operate an energy system based on varying demands. This approach takes account of investment costs, operating costs of units for all periods, and the planning for scheduled maintenance of equipment. Yoshida et al. (2007) proposed a mathematical optimisation method to determine the optimal system structure and operational strategy for tri-generation system for a hospital. In this work (Yoshida et al., 2007), a sensitivity analysis was also performed on uncertainties related to energy prices and decline in equipment costs. Meanwhile, Aguilar et al. (2007a,b) presented a systematic methodology which is able to simultaneously synthesise, design and optimise the capital investment of a co-generation system subject to variable design conditions. Dimopoulos et al. (2008) presented an approach which uses EA to solve the synthesis, design and operation optimisation of a marine co-generation system.

Apart from that, Buoro et al. (2010) presented an optimisation model to determine the optimal synthesis and operation of an urban tri-generation system based on total annual costs of operations. The optimisation specifies the kind, number and location of the tri-generation technologies as well as the optimal strategy in which it would operate at. Buoro et al. (2011) then extended this work by proposing a model which determines the optimal tri-generation system based on varying amortisation periods. Later, Buoro et al., (2012) presented a model which obtains the optimal synthesis, design and operation of a co-generation systems for standard and domotic homes. A sensitivity analysis was performed by introducing different economic constraints. Mehleri et al. (2013) presented a mathematical optimisation-based approach to synthesise an optimal residential co-generation system. The optimal residential co-generation system is determined by minimising the total energy costs, taking into account the site energy demands, local climate data, geographical aspects and utility tariff structure. Wakui and Yokoyama (2014) developed a multi-period optimisation approach which minimises the purchased power and natural gas consumption of co-generation units in a Japanese residence. Ghadimi et al. (2014) presented a mathematical approach to select an optimal on-site co-generation system for a pharmaceutical manufacturing plant. The proposed methodology performs design sizing while selecting among thermal load and electric load following operational strategies. More recently, Arcuri et al. (2015) presented an iterative optimisation approach for determining the optimal design of a tri-generation system based on return of investment subject to technology, size, and daily operations. The iterative optimisation approach also quantifies and compares the total earnings achievable to conventional designs which use the electrical grid to satisfy electrical needs and a traditional boiler to satisfy thermal needs.

On the other hand, several works have considered economic and environmental aspects simultaneously. For instance, Carvalho et al. (2012a) presented a multi-criteria approach for the synthesis and operation of tri-generation systems considering environmental and economic aspects. In this work (Carvalho et al., 2012), optimal solutions are obtained and analysed via a Pareto Front. This work was then extended by incorporating a sensitivity analysis on electricity prices toward the optimal configuration (Carvalho et al., 2013). Similarly, Buoro et al. (2013) developed a MOO approach to obtain the optimal structure, capacity and operational strategy of an industrial co-generation system. The MOO approach considers a weighted combination of annual costs (e.g., for owning, maintaining, and operating the whole system) and the associated CO_2 emissions. Meanwhile, Luo et al. (2014) developed a MOO approach that minimises economic cost and environmental effect while maximising exergy efficiency of a go-generation system. The approach determines equipment type, equipment number, equipment design capacity, and equipment operation load using the ε-constraint method.

Despite the aforementioned contributions, it is found that equipment reliability has not been considered during the synthesis of an energy system. Reliability is an important aspect as it considers the probability and availability of a given equipment to perform its functions. Equipment generally consists of parts that would require regular preventive or corrective maintenance, which would inhibit overall system performance. Section 2.6 discusses the importance of reliability considerations in energy systems design and reviews previous works that have incorporated it.

2.6 Reliability Aspects in Synthesis of Energy Systems

As described in Section 2.5, it is important to consider synthesis, design and operation aspects simultaneously when designing an energy system. These aspects can be exploited to establish a design that would feature technologies with different process units integrated with each other to meet specified energy demands. Integration of process units enables such systems to achieve higher thermodynamic efficiency levels and economic performance as compared to conventional stand-alone systems. However, such benefits may not be realised if an energy system is not equipped to cope with failure of its component process units. Since an energy system contains a network of interconnected and interdependent equipment, a failure event can cause “ripple effects” to propagate throughout the system and disrupt the overall performance. Furthermore, planned stoppages of operations for preventive maintenance of equipment also need to be considered, along with unplanned equipment failure which then requires corrective maintenance. As such, it is necessary to consider during design whether an energy system will be capable of meeting energy demands in the event of failure. Such issue is an important aspect in designing energy systems, as it has implications on the operational reliability of delivering energy supply to the end-user processes.

Reliability is defined as the probability that a system will perform a required function at a given point in time, when operated under specific conditions (Ebeling, 1997). In other words, it is a quantitative measure (e.g., percentage) of non-failure operation over a given (operational) time period. Since no equipment can ever be fully (100%) reliable, it is necessary to account for the possible failures during the synthesis and design optimisation stages. It is essential that the design possesses a level of preparedness or robustness toward failures which may occur during operations (Schock et al., 2012). A common way of addressing such issue is providing redundancy (Kuo and Zhu, 2012).

Redundancy allocation is a strategy of employing additional equipment units connected in parallel to perform the same function, with the intention of achieving higher system reliability. Traditionally, redundancy cases were considered by means of heuristics. For example, the $n + 2$ rule is a heuristic applied where two extra units are added to an initial design specification, n, where redundancy was not considered (Aguilar et al., 2008). Besides implementing additional units, safety or design factors have been used for specifying excess capacity for equipment within an energy system in order to cope with disruptions during operations. Such heuristics have been applied extensively in the past. For example, Varbanov et al. (2004) applied the heuristic of where the sum of all boiler sizes is designed to be 30% higher than the steam requirement in order to design an energy system. Recently, Maheri (2014) used safety factors to determine the optimal size of a hybrid renewable energy system considering multiple configurations. For each considered configuration, different safety factor values were used to find the optimal size of the system components which minimises the system cost deterministically. Then, for each case, Monte Carlo simulation was used to study the effect of safety factors on the reliability and the cost. In performing reliability analysis, several reliability measures (e.g., unmet load, blackout durations and mean time between failures) were considered. Despite its simplicity of application, heuristics often depend on the experience of the designer. The empirical overdesign as a solution to ensure a reliable energy system is not attractive from the economical viewpoint and there is no guarantee of achieving efficient operation. Moreover, conservative design based on the worst operating conditions, may fail because the proper selection is far from trivial and what is deemed as logical choices, may lead to systems with higher costs (Grossmann and Morari, 1984).

Aside from heuristic approaches, mathematical optimisation approaches have been employed to address reliability aspects without pre-defining any redundancy. For instance, Olsommer et al. (1999a;b) proposed a methodology to optimise the design and operation of a co-generation system subject to different operating scenarios. The approach also performs a reliability analysis via Markov chain analysis, and is able to determine all the possible failure modes once the optimal system is defined. Frangopoulos and Dimopoulos (2004) then extended the previous work by using the same steps, but all within one optimisation procedure. In this approach, an energy system design is first proposed using genetic algorithm (GA). Reliability analysis is simultaneously carried out by generating possible failure scenarios and subsequently calculating penalties whenever energy demands are not fully met. The corresponding investment and operating costs are then compared with the designs automatically generated from the search procedure, until a near-optimal solution is found. Del Nogal et al. (2005) developed a model for the design of energy plants for power-intensive processes. The model developed by Del Nogal et al. (2005) directly includes expected down time for different equipment types, sizes and configurations, and thus allows capital costs, operating costs and loss of profit to be considered simultaneously. Aguilar et al. (2008) extended the previous works (Aguilar et al., 2007a, 2007b) to address the design and operation of a co-generation system by incorporating reliability issues using a robust optimisation framework. The approach was presented for both grassroots design and retrofit problems. In addition, the framework (Aguilar et al., 2008) determines the redundancy allocation for the system based on different time horizons and failure scenarios. Later, Lin et al. (2012) proposed a methodology which combines operation and design optimisation of an energy system by incorporating reliability theory based on Markov chain analysis. Luo et al. (2013) presented a systematic methodology to address equipment failure for an existing steam power plant in a petrochemical complex with operation redundancy. Their methodology minimises total costs under normal operating conditions while reserving sufficient flexibility and safety for unexpected equipment failure.

Apart from that, Voll et al. (2013) presented a framework on automated superstructure generation and optimisation of a tri-generation system. Based on different demands, available technologies and topological constraints, their framework first employs P-graph approach to generate an initial superstructure of technological alternatives. Then, a successive approach is employed to automatically expand the initial P-graph superstructure to account for multiple redundant units. The expanded superstructure is then automatically converted into a mathematical model using a generic component-based modelling approach. The model is then used to optimise the structure, size and operations of a tri-generation system. More recently, Sun and Liu (2015) proposed an approach based on simultaneously modelling and optimising the structure and operation of a steam and power plant system with Markov Chain reliability analysis. A multi-period stochastic model is proposed considering compensation costs and penalty costs to obtain both system configuration with spare equipment (and spare capacities) and operating scheduling specification for equipment failures and process demand fluctuations. Meanwhile, Godoy et al. (2015) developed an optimisation strategy to quantify the impact of availability and maintenance during the early stages of synthesis and design of a new combined cycle power plant. A detailed state-space approach is used to account the influence of maintenance funds on equipment's repair rate. Recently, Rad et al. (2016) presented an integrated methodology that combines process integration tools (e.g., TSA, exergoeconomic analysis, etc.) with reliability and availability analysis for the design of energy systems. The integrated methodology uses reliability (e.g., failure and repair rates) as a performance parameter for optimise exergetic and economic objectives. Besides energy systems, reliability issues has been considered in other areas such as chemical process synthesis (Goel et al., 2003, 2002), heat exchanger network synthesis (Grossmann and Morari, 1983; Yi et al., 2013) and waste management (Sikos and Klemeš, 2009).

The aforementioned literature suggests significant opportunities to further develop systematic approaches to address reliability aspects in energy systems. Firstly, there is a need for a more rigorous, non-heuristic approach which nevertheless remains computationally efficient. Secondly, a more comprehensive, systematic approach is required to address complex decisions pertaining to installation of multiple additional units for higher system reliability. Specifically, the choice to be addressed is whether to install a small number of large units, or a larger number of smaller units. This is an important issue that should be considered because each option offers unique advantages and disadvantages. Also, such decisions become increasingly complex when seasonal variations in raw material supply and energy demand are considered. If such decisions are not addressed appropriately, an energy system may perform sub-optimally during certain operational periods, and incur excessive capital and maintenance costs. It is also noted that design operability has received limited attention. Design operability is important as it allows designers to analyse if proposed designs are capable of meeting its intended operations, especially during equipment failure. This will consequently allow designers to proceed by considering foreseeable energy demand changes in the future. If provisions are required, designers can look into debottlenecking and retrofitting the system design. The next section the reviews the concept of operability, flexibility and retrofit as well as previous systematic approaches presented in these areas.

2.7 Operability, Flexibility and Retrofit of Energy Systems

Operability is the ability of a process to cope with disturbances scenarios (e.g., reliability issues) and meet performance criteria defined in the design phase (Sharifzadeh, 2013). Meanwhile, flexibility is defined as the ability of a process to achieve feasible operation over a range of uncertainties (Svensson et al., 2015). According to Grossmann and Westerberg (2000), the field of PSE can perform operability analysis by mathematically proving some useful properties or empirically demonstrate that a proposed model works for a set of example problems. This will consequently allow designers to proceed on decisions regarding foreseeable energy demand changes in the future. Designers can thereupon make provisions in the current system design so that it is sufficiently flexible to accommodate for these changes, after it has been put into operation. These provisions include retrofitting the system design.

Retrofit refers to a process in which existing capacity is upgraded by implementing energy-efficient technologies or measures such as increasing capacity (Worrell and Biermans, 2005). The decision to retrofit a process can arise when equipment bottlenecks are present in a process. An equipment is considered a bottleneck when it is required to increase its throughput, but unable to do so due to restrictions in feedstock and equipment (design capacity) specifications, insufficient energy supply, or sub-optimal operating conditions and equipment efficiencies. It is common for an energy system to undergo a steady increase in energy demand with the growing technology and/or business development. Such growth imposes a great challenge to designers and researchers, as this entails increased energy production.

Debottlenecking is a classical approach of modifying existing equipment to remove throughput restrictions and achieve a desired performance that a system is presumed impossible with its current configuration (Schneider, 1997).

Several works have explored and presented effective approaches for identifying bottlenecks and debottlenecking processes from various backgrounds. For instance, Harsh et al. (1989) presented a work that identifies the process bottlenecks with flowsheet optimisation strategy. It was done prior to applying an MINLP model to retrofit an ammonia process. Diaz et al. (1995) used an MINLP model to determine the optimal configuration and operating conditions of an ethane extraction plant by introducing minor plant structural modifications. On the other hand, Voudouris and Ariston Consulting (1996) developed a large scale MILP model for the fine chemical industry. The model helped to identify production bottlenecks and subsequently debottleneck the supply chain in the case of schedule and throughput enhancement. Later, Litzen and Bravo (1999) proposed the “stair-step chart” to visualise the cost-benefit ratio of each step progressively towards the debottlenecking goal. In their work, the analysis emphasised on the interactions among process units, instead of individual units.

On the other hand, Ahmad and Polley (1990) attempted to debottleneck a heat exchanger networks (HENs) with the use of pinch analysis. This method predicts the least requirement of energy and capital where HEN retrofit is done for increased throughput. Another attempt of HEN debottlenecking by considering realisation of pressure drop optimisation procedure was also performed (Panjeshi and Tahouni, 2008). The optimisation procedure optimised the additional area and the operating costs involved in the HEN, and was validated against a crude oil pre-heat train subjected to a 20% throughput increase. Alshekhli et al. (2010) used a computer-aided process simulation tool to model and debottleneck an industrial cocoa manufacturing process. This work was focused on increasing the cocoa production rate and determining an economically viable production scheme. Other works that also used process simulations for debottlenecking of batch processes include Koulouris et al. (2000). It presented a systematic simulation-based methodology for identifying bottlenecks in a synthetic pharmaceutical batch process as well as a strategy for eliminating them. Meanwhile, Tan et al. (2006) also presented a debottlenecking strategy for batch process in pharmaceutical industry via process simulation.

Most recently, Tan et al. (2012) developed a methodology for the identification of bottlenecks in continuous process plants that can be described by a system of linear equations. This algebraic approach is based on the concept of inoperability or more readily known as inoperability input-output modelling (IIM). IIM is an approach proposed by Haimes and Jiang (2001) to analyse the failure of interdependent infrastructure systems (described by a system of linear equations) suffering from disruption events. Later, Kasivisvanathan et al. (2013) adapted IIM to determine the optimal operational adjustments when disruptions occur in multi-functional energy systems. Kasivisvanathan et al. (2014) extended the previous work to develop heuristic frameworks for designers to identify bottlenecks in a palm oil-based biorefinery, especially when variations in supply and production demand are considered. Despite the usefulness of the aforementioned contributions, it is observed that the effect of change in equipment efficiency over time has not been considered during debottlenecking.

Before debottlenecking, it is important to consider that equipment operating over a period of time would experience changes in efficiency for two reasons. Firstly, the drop in efficiencies may affect the overall system reliability. For instance, if a unit experiences reduced efficiency, it may not be able to respond adequately when other units undergo failure, hence disrupting the overall system reliability when failures occur. Secondly, the reduced equipment efficiency would result in a different overall system performance as compared to when it was first designed. This would mean that targeted energy demands may lie outside the range in which the operating energy system is capable of delivering, hence causing an infeasible operation. Neglecting these factors would only prove costly as decision making procedures would be made based on inaccurate representation of the system performance.

Aside from operational aspects, the economic performance of an energy system can be analysed further based on its interaction with end-users. Since heat, power and cooling energy are essentially required in most industrial processes, energy systems can be more economically attractive if synthesised for an industrial park. The next section the reviews the concept of EIPs as well as previous systematic approaches presented on EIPs.

2.8 Energy Systems for Eco-Industrial Parks

As mentioned previously, energy systems have the potential to be more economically attractive if synthesised for an eco-industrial park (EIP). Prior to EIPs, Frosch and Gallopoulos (1989) introduced the concept of industrial ecology (IE), which is based on analogies with symbiotic flows in natural ecosystems. IE emphasises on the importance and the potential benefits of symbiotic interactions among various companies. For instance, waste generated from one production process may be used as raw materials in another process. When successfully implemented, IE would reduce overall waste and emission from the entire system as well as the raw material and energy consumption to other systems (Korhonen, 2001). Since such symbiotic relationships normally occur among processes co-located within the same vicinity, the concept of EIPs emerged (Lowe et al., 1996). Due to geographic proximity, plants in an EIP are more likely to cooperate through infrastructure, material, water and energy exchange programs. As a result, the collective benefit will always be greater than the sum of individual benefits that could be achieved without establishing a symbiotic relationship in an EIP. In this respect, several systematic approaches have been developed for designing shared infrastructure in EIPs (Boix et al., 2015).

One type of shared infrastructure found in literature is inter-plant water integration in EIPs (Boix et al., 2015). In the area of inter-plant water integration, several contributions focused on minimising fresh water (Chew and Foo, 2009), regeneration and waste treatment flow rates (Chew et al., 2010a, 2010b) and emergy (Taskhiri et al., 2011). Other works focused on minimising environmental impacts

(Lim and Park, 2010) and total annualised costs (López-Díaz et al., 2015). More recently, Aviso (2014) presented a robust optimisation approach to determine the optimal inter-plant water network which can operate under multiple probable scenarios such as changes in process conditions, number of plants, water quality, etc.

Besides inter-plant water networks, several contributions have considered the designing energy networks for an EIP (Boix et al., 2015). These energy networks include waste heat network (Chae et al., 2010), utility network (Kim et al., 2010), biorefineries (Atkins et al., 2011), steam power plant (Chen and Lin, 2012), palm oil processing complex (Ng and Ng, 2013) and central utility system (Liew et al., 2013) using Total Sites integration (Dhole and Linnhoff, 1993). Meanwhile, other contributions focused on aspects such as improving production (Gonela and Zhang, 2014) and analysing criticality of systems (Benjamin et al., 2014; Michael Francis D. Benjamin et al., 2015) in bioenergy-based EIPs. However, aforementioned EIPs may prove unsuccessful if the self-interest of each participating plant is not met. In reality, every participant plant in an EIP has unique individual goals that may conflict with other potential partners (Jackson and Clift, 1998). This aspect is not adequately addressed by many conventional PSE techniques derived from Process Integration (PI) approaches.

Nevertheless, a small number of contributions have proposed mathematical optimisation models which consider satisfaction of participants in EIPs. For instance, Aviso et al. (2010a, 2010b) presented a bi-level fuzzy optimisation model for optimising water, wastewater reuse in an EIP based on individual goals of each participant and introduced the role of an external agent (government) to induce cooperation among companies. Taskhiri et al. (2014) developed a similar approach to optimise allocation of waste-to-energy streams in an EIP. Ng et al. (2013) presented a fuzzy programming approach to consider the individual targets of multiple owners instead of just one owner. This approach is then extended to disjunctive fuzzy programming to determine the optimum pathways based on each owner's targets and allow withdrawal if any target is not satisfied (Ng et al., 2014). Wang et al. (2013) introduced a novel approach for analysing the stability of EIP system based on the equitable distribution of symbiosis profit and cost. They defined stability as the tendency of the coalition of companies in an EIP to remain intact based on equitability considerations. The asymmetric distribution coefficients of each participating plant are calculated and the IE system is considered stable as long as asymmetric distribution coefficients are within the agreed range. This approach implies that an IE system is stable for as long as no partner bears a disproportionate share of symbiosis costs relative to benefits gained from cooperation; otherwise, a firm which finds itself in an unfavourable position becomes liable to withdraw from the coalition. Such approach is later adapted by Ng et al. (2015) to analyses the stability of each participating plant in a palm oil processing complex (POPC) in Ng et al. (2014).

Besides mathematical optimisation approaches, Game theory-based approaches have been presented for decision making in EIP schemes. Game theory is a suitable framework that mathematically models the behaviour of multiple agents with potentially conflicting interests in various domains (von Neumann and Morgenstern, 1944). As such, several studies have been directed toward Game theory-based approaches for effective decision making in various EIP schemes. For instance, Chew et al. (2009) demonstrated how incentives play a role in inducing cooperation to yield Pareto optimal solutions in an EIP. On the other hand, Hiete et al. (2012) proposed a cooperative game theory approach based on the Shapley value (Shapley, 1953) to allocate energy savings between partners based on their marginal contributions in a pulp and woody bio-energy EIP scheme. Zhang et al. (2013) presented mathematical formulation based on the game theory Nash bargaining solution approach to fairly determine cost allocation amongst facilities in a general micro-grid. However, allocating benefits alone would be inadequate to guarantee a stable EIP coalition.

Stability in the context of EIPs, refers to the robustness of an EIP coalition toward changes in costs associated with investment and operations (Holling, 1996; Kronenberg, 2007; Mayer, 2008). In a coalition, each plant is prone to deviations in symbiosis costs. Symbiosis cost is the investment cost that each plant requires to engage in material and energy exchange with other plants in an EIP. Symbiosis costs may include expenditure on transportation, piping and instrumentation, shipment, labour, conveyor systems, etc. If deviations in symbiosis costs are ignored, changes in profit margins may cause dissatisfaction among plant stakeholders and consequently disrupt the overall stability of the coalition.

2.9 Summary of Research Gaps

Despite the usefulness of the works reviewed in Sections 2.1 – 2.8, five important research gaps are noted. As mentioned in Section 1.1, biomass is identified as a potential source of sustainable energy. Such energy potential can be recovered in energy systems on-site to reduce costs of importing energy and improve overall energy conversion efficiency. In this respect, there is a need for systematic approaches to design a biomass-based energy system (BES).

Firstly, energy systems are conventionally designed by carrying out synthesis, design and operation optimisation in a hierarchical manner. Unfortunately, this approach presents a drawback as system operations and its corresponding uncertainties have a direct influence on the solution from design and synthesis. In view of this, an integrated approach to design energy systems was proposed. The integrated approach suggests that synthesis, design and operation optimisation tasks is performed in parallel with each other, to design an energy system. However, past approaches presented in this area have not considered aspects such as seasonal biomass supply and energy demands to design an energy system.

Secondly, it is worth noting that equipment redundancy allocation in an energy system has received very limited attention. According to literature, heuristics are conventionally adapted to employ redundancy in an energy system design. Besides heuristics, several optimisation approaches have also been presented to address reliability of energy systems. However, there is a need for a more rigorous yet less computationally intensive approach to address redundancy allocation issues in energy systems. Furthermore, a more comprehensive systematic approach is required to address complex decisions such as whether to install additional large capacity units or multiple smaller capacity units. This is an important issue that should be considered as each option is unique in terms of equipment reliability. Besides, redundancy allocation decisions become increasingly complex when seasonal variations in raw material supply and energy demand are also factored in. If such decisions are not addressed appropriately, an energy system may perform sub-optimally during certain operational periods and incur unnecessary or excessive capital and maintenance costs.

Thirdly, it is found that there is limited work combining design and switching operation strategy considerations for an energy system. This is evidently shown in most efforts that developed switching operating strategies based on PEC without explicitly taking into account its corresponding technology selections, sizing and capital costs, and vice versa. Typically, energy systems with switching strategies are designed by combining technologies from both FEL and FTL designs into a unified layout. However, such design would be unfavourable due to its potentially high capital costs. As such, incorporating operating strategy considerations during the design phase would prevent unnecessary capital expenditure for a BES.

Fourthly, it is noted that design operability and flexibility has received limited attention. Design operability and flexibility are important aspects in designing energy systems as it allows designers to determine if proposed designs are capable of meeting their intended operations especially during failure scenarios. This will consequently allow designers to proceed by considering foreseeable energy demand changes in the future. If provisions are required, several works have considered debottlenecking and retrofitting the system design. However, these works have yet considered the effect of changes in efficiency for equipment operating over a period of time. This aspect is essential for two reasons. Firstly, the drop in efficiencies may affect the overall system reliability. For instance, if a unit experiences reduced efficiency, it may not be able to respond adequately when other units undergo failure, hence disrupting the overall system reliability when failures occur. Secondly, the reduced equipment efficiency would result in a different overall system performance as compared to when it was first designed. This would mean that targeted energy demands may lie outside the range in which the operating energy system is capable of delivering, hence causing an infeasible operation. Neglecting these factors would only prove costly as decision making procedures would be made based on trivial assumptions of the system performance.

Lastly, several works have explored the concept of eco-industrial parks (EIPs). Based on the review, a small number of works use Game theory as a basis of allocating benefits (e.g., incremental profits, savings, credits, etc.) among plants in an EIP. However, it is observed that economic stability of these allocations in an EIP has received limited attention. This is important as, each plant in an EIP is prone to deviations in symbiosis costs (e.g., transportation, piping and instrumentation, shipment, labour, conveyor systems, etc.). If deviations in symbiosis costs are neglected, changes in profit margins may cause dissatisfaction among plant stakeholders and consequently disrupt the overall stability of the coalition. By analysing the economic stability, stakeholders of each plant would be able to make informed decisions on whether to invest or participate in an EIP project.

The aforementioned gaps serve as motivation for this research work. To address these research gaps, several research scopes and methodologies are proposed in Chapter 3.

CHAPTER 3

SCOPES AND METHODOLOGY OF RESEARCH

3.1 Research Scopes

Section 2.9 pointed out several research gaps. To address the aforementioned research gaps, this research is organised to develop systematic approaches that consider the following scopes;

3.1.1 Scope 1

Synthesis of Biomass-based Energy Systems with Variations in Biomass Supply and Energy Demand

In Scope 1, a systematic approach is developed to synthesise and design of a biomass-based energy system (BES) based on seasonal variations in biomass supply and energy demand. A multi-period optimisation approach is developed to consider variations in raw material supply and corresponding energy demand. In addition, selection of design capacities based on available sizes in the market is also performed simultaneously.

3.1.2 Scope 2

Synthesis and Optimisation of Biomass-based Energy Systems with Reliability Aspects

The approach presented in Scope 1 is then extended to consider reliability aspects of the BES for Scope 2. A novel systematic approach is presented to synthesise a reliable grassroots BES design considering allocation of equipment redundancy. The presented approach considers the possibility of installing either large capacity equipment or multiple smaller capacity units based on their unique equipment reliabilities.

3.1.3 Scope 3

Synthesis of Biomass-based energy systems: Technology Selection, Sizing and Redundancy Allocation based on Operational Strategy

Scope 3 extends Scope 2 to consider the operational strategy of the BES. A systematic approach is developed to synthesise a BES robust towards its operating strategies. The developed approach aims to simultaneously perform selection of technology, sizing of equipment and redundancy allocation to cope with equipment failure within the system based on operational strategies considered.

3.1.4 Scope 4

Systematic Approach for Design Operability Analysis (DOA) of Biomass-based Energy Systems

In Scope 4, a systematic framework for Design Operability Analysis (DOA) is developed to analyse BES designs synthesised. This framework will perform disruption scenario analysis to study and determine if a BES design is able to cope with equipment failure. In addition, the framework will also analyse the overall feasible operating range of the BES design and determine if the BES design is capable of meeting its intended seasonal operation especially in the instance of failure.

3.1.5 Scope 5

Systematic Approach for Design Retrofit Analysis (DRA) of Biomass-based Energy Systems

After Scope 4, informed decisions can be made on whether debottlenecking is required for future energy demand variations. In the case where future energy demand variation plans are considered, a decision making framework on Design Retrofit Analysis (DRA) is developed in Scope 5 to undertake debottlenecking procedures in order to retrofit an existing BES for future demand variations.

3.1.6 Scope 6

An Optimisation-based Negotiation Framework for Energy Systems in an Eco-industrial Park

In Scope 6, an optimisation-based negotiation framework is developed to analyse the potential cost savings allocation between participating facilities in an eco-industrial park (EIP) scheme. This framework will combine the principles of rational allocation of benefits with the consideration of stability and robustness of the coalition to changes in cost assumptions.

In order to explore these scopes, the methodology for this research is described in Section 3.2.

3.2 Research Methodology

The proposed research scopes are explored based on a research methodology shown in Figure 3.1. Firstly, an extensive literature review is carried out to compile and enumerate all possible unit operations relevant to a BES. Subsequently, information regarding these listed options (e.g., feedstock, intermediate products, final products, operation data, conversions and consumption, etc.) are collected. With the gathered information, a superstructure representation connecting all individual unit operations is developed. Following this, the behaviour and performance of the listed unit operations are mathematically modelled and solved based on the approaches developed for each respective research scope.

Chapter 4 presents the synthesis of a BES based on uncertainties in biomass supply and energy demand. In this work, a multi-period optimisation approach is developed to perform technology and design capacity selection for a BES while considering seasonal biomass supply and energy demand profiles in multiple scenarios. To illustrate the proposed approach, a tri-generation system with palm-based biomass as feedstock is solved in Chapter 4.

Chapter 4 is then extended in Chapter 5 to consider the reliability of technologies for a BES. The extended approach in Chapter 5 systematically allocates equipment redundancy for a BES design based on their unique reliabilities. In this chapter, chance-constrained programming and *k*-out-of-*m* system modelling are used to develop a multi-period optimisation model to simultaneously screen technologies based on their respective equipment reliability, capital and operating costs. The model also determines equipment capacities, along with the total number of operating (and stand-by) equipment based on various anticipated scenarios in a computationally efficient manner. Two palm-based biomass case studies are solved to illustrate the approach presented in Chapter 5.

In Chapter 6, a systematic approach is developed to synthesise a BES robust towards its operating strategy. The developed approach extends Chapter 5 to simultaneously perform selection of technology, the sizing of equipment and redundancy allocation within the system considering various operating strategies (e.g., FTL, FEL, etc.). A palm BES case study is solved to illustrate the proposed approach.

Following Chapter 6, Chapter 7 present a systematic framework on DOA to analyse proposed BES designs. DOA looks at analysing the maximum possible level of operability for the BES and also determines how a BES performs during failure. DOA two important steps; the disruption scenario analysis (DSA) and the feasible operating range analysis (FORA). In DSA, equipment failure scenarios are studied to determine if a synthesised BES design configuration is able to remain operable, despite facing disruptions from within. Meanwhile, the FORA studies the inherent feasible operating range of the synthesised BES. The feasible operating range is a range of net utility output a BES can deliver without experiencing design and performance limitations. This range allows designers to recognise the true operating potential of the system and use it to validate its performance for intended seasonal energy demands. To illustrate the proposed framework, the palm BES design from Chapter 5 is used as a case study.

Next, Chapter 8 presents a systematic approach on DRA to debottleneck existing BES designs when energy demand variations are anticipated in the future. This approach extends the work in Kasivisvanathan et al. (2014) by incorporating DSA and FORA. Unlike Chapter 7, the DSA and FORA is used to re-analyse an existing BES's capability of coping with equipment failure and its real-time feasible operating range respectively. By doing so, designers will be well informed to decide whether an existing system requires debottlenecking. In the case where a system requires debottlenecking, Chapter 8 provides a step-by-step guide to debottleneck and retrofit procedures. To illustrate the proposed framework, the palm BES case study from Chapter 5 is extended in Chapter 8.

Lastly, Chapter 9 looks into the economic viability of a BES. In this chapter, an optimisation-based negotiation framework is proposed to aid plants to investigate their cost savings in an EIP based on their respective contributions. This framework applies a cooperative game model (Maali, 2009) to rationally and fairly allocate the pooled cost savings to each participating plant in an EIP. Next, this framework extends the stability analysis developed by Wang et al. (2013) to investigate the stability threshold of each plant in an EIP. The stability threshold indicates the range of symbiosis investment (e.g., transportation costs, piping and instrumentation costs, shipment costs, labour costs, conveyor system, etc.) each plant can absorb in order to be stable in the EIP. Moreover, the stability threshold can function as a basis of negotiation when symbiosis costs fall outside the stability range or when changes in operational costs are anticipated in the future. To demonstrate this framework, a palm oil eco-industrial park (PEIP) case study is solved in Chapter 9.

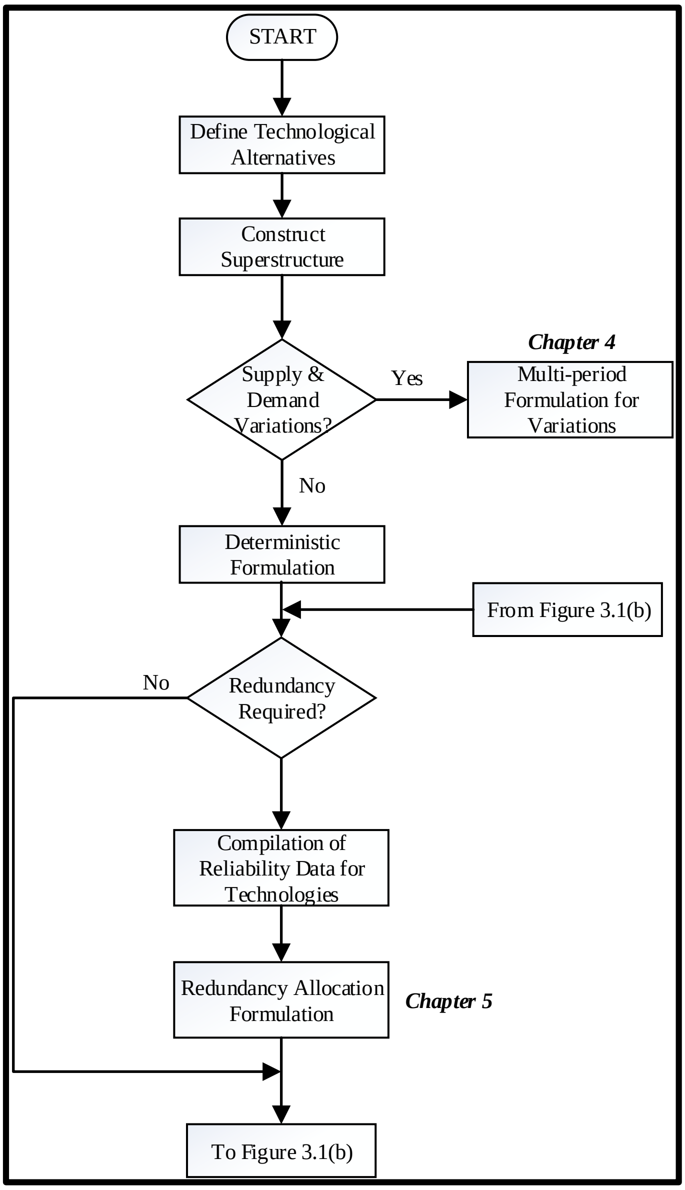

Figure 3.1: (a) Research Methodology

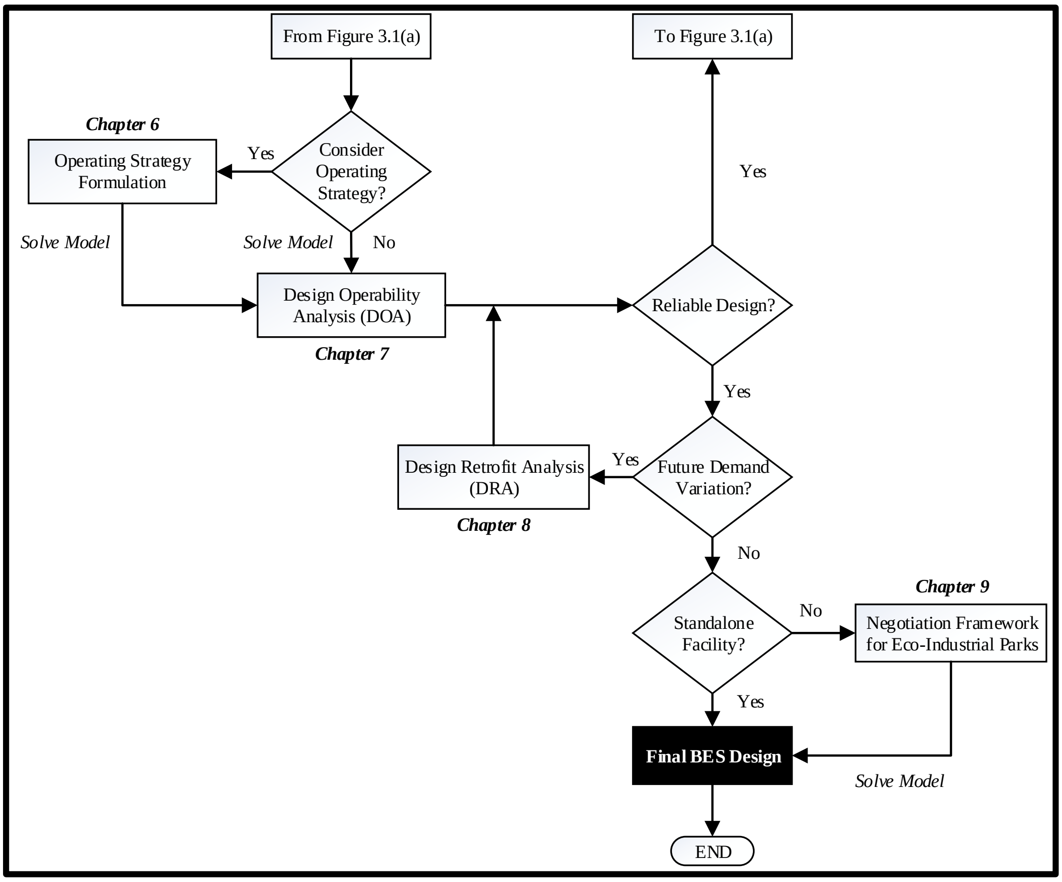

Figure 3.1: (b) Continued

CHAPTER 4

SYNTHESIS OF BIOMASS-BASED ENERGY SYSTEMS WITH VARIATIONS IN BIOMASS SUPPLY AND ENERGY DEMAND

4.1 Introduction

As mentioned in Section 2.2, a biomass-based energy system (BES) produces heat, power and cooling energy simultaneously from biomass feedstock. To synthesise a BES, decision makers are required to consider a wide range of technologies based on various factors (e.g., capital investment, operating cost, availability and reliability of the technologies, etc.). In addition, both short-term and long-term uncertainties which may arise during the course of operations should also be taken into consideration. If not considered at the synthesis stage, uncertainties would prevent the designed energy system from meeting the required energy demands and cause possible bottlenecks during operation. With such consideration, not all available technologies are economically and operationally sensible. Thus, Chapter 4 presents a multi-period optimisation approach for the systematic synthesis of a BES with variations in raw material supply and corresponding energy demand. In the multi-period optimisation approach, the fraction of occurrence for each biomass supply and energy demand scenario is included. Meanwhile, the maximum capacities of each technology that can operate in all scenarios are determined. In addition, selection of design capacities based on available sizes in the market is also performed simultaneously. To illustrate the proposed approach, a tri-generation system with palm-based biomass as feedstock is solved in this chapter.

4.2 Problem Statement

As various established technologies are available in the market, the synthesis of a BES is a highly complex problem. Generic representation of the problem is shown in Figure 4.1. The synthesis problem addressed is stated as follows: Biomass i with flow rate F_i^{BIO} and its composition $q \in Q$ (e.g., lignin, cellulose, and hemi-cellulose), can be converted to primary product $p \in P$ through technologies $j \in J$. Primary product p and its composition $q' \in Q'$ can be further converted to final products $p' \in P'$ via technologies $j' \in J'$. Besides producing primary and final products p and p', technologies j and j' can also generate energy $e \in E$. In Chapter 4, the objective is to develop a systematic approach to synthesise a robust BES configuration with maximum economic performance while considering multiple supply and demand scenarios, $s \in S$. In addition, the proposed approach able to determine the optimum design capacities of the selected equipment based on the maximum operating capacity of all scenarios. As most of the available equipment sizes in the market are fixed, the proposed approach can also select the equipment based on the available design capacities of technologies j $\left(\mathrm{F}_{jn}^{\mathrm{Design}}\right)$ and j' $\left(\mathrm{F}_{j'n'}^{\mathrm{Design}}\right)$ respectively. The aforementioned optimisation model is then solved via multi-period optimisation whereby each scenario s is assigned a fraction of occurrence, α_s.

The following section further explains parameters and variables involved in the optimisation model developed for this work. The equations formulated in the optimisation model are clearly presented and described methodically to address the BES synthesis problem.

4.3 Mathematical Optimisation Formulation

The generic superstructure of a BES is shown in Figure 4.1. Based on Figure 4.1, the following Sections 4.3.1 – 4.3.3 present a detailed formulation of the proposed multi-period optimisation model.

4.3.1 Material Balance

As mentioned previously, it is important to consider uncertainties in seasonal raw material supply and energy demand for the synthesis of a BES. To consider such uncertainties, this work considers multiple raw material supply and energy demand scenarios (as shown in Figure 4.2). Each scenario is a quantitative projection of the relationship between inputs and outputs. With such consideration, decision makers are able to synthesise a feasible BES configuration which is robust to potential changes (or uncertainties). In this work, each scenario considered is represented by index *s*. For each scenario *s*, each biomass *i* consists of lignocellulosic components *q* such as lignin, cellulose, and hemi-cellulose. Note that different types of biomass can be represented with the different composition of lignocellulosic components. Therefore, in this work, a robust BES which handles multiple feedstocks can be synthesised.

Equation 4.1 shows the component balance for biomass *i* where f_{iq}^{BIO} and θ_{iq} are the component flow rates and compositions respectively. Besides, F_i^{BIO} represents the total flow rate of biomass *i*.

$$\left(f_{iq}^{\mathrm{BIO}}\right)_s = \left(F_i^{\mathrm{BIO}}\theta_{iq}\right)_s \qquad \forall i \forall q \forall s \qquad (4.1)$$

Each biomass i is allocated to potential technology j with flow rate of F_{ij}^{I} as shown;

$$\left(F_i^{\mathrm{BIO}}\right)_s = \left(\sum_{j=1}^{J} F_{ij}^{\mathrm{I}}\right)_s \qquad \forall i \forall s \qquad (4.2)$$

In process technology j, the flow rate of component q in biomass i is given by Equation 4.3

$$\left(f_{qj}^{\mathrm{I}}\right)_s = \left(\sum_{i=1}^{I} F_{ij}^{\mathrm{I}}\theta_{iq}\right)_s + \left(\sum_{p=1}^{P} F_{pj}^{\mathrm{I}}\theta_{pq}\right)_s + \left(\sum_{p'=1}^{P'} F_{p'j}^{\mathrm{I}}\theta_{p'q}\right)_s \qquad \forall q \forall j \forall s \qquad (4.3)$$

where

$$\sum_{q=1}^{Q} \theta_{iq} \leq 1 \qquad \forall i \qquad (4.4)$$

Component q is then converted to primary products p with the conversion of $\mathrm{X}_{qjp}^{\mathrm{I}}$ respectively as shown in Equation 4.5.

$$\left(F_{jp}^{\mathrm{I}}\right)_s = \left(\sum_{q=1}^{Q} f_{qj}^{\mathrm{I}}\mathrm{X}_{qjp}^{\mathrm{I}}\right)_s \qquad \forall p \forall j \forall s \qquad (4.5)$$

The total production rate of primary product p for all process technologies j is given as;

$$\left(F_p^{\mathrm{Ret}}\right)_s + \left(F_p\right)_s = \left(\sum_{j=1}^{J} F_{jp}^{\mathrm{I}}\right)_s \qquad \forall p \forall s \qquad (4.6)$$

Meanwhile, p can be recycled back to technology j with total flow rate F_p^{Ret}. F_p^{Ret} can then be allocated to technology j as shown;

$$\left(F_p^{\mathrm{Ret}}\right)_s = \left(\sum_{j=1}^{J} F_{pj}^{\mathrm{I}}\right)_s \qquad \forall p \forall s \qquad (4.7)$$

where F^{I}_{pj} is flow rate of primary product *p* recycled to *j*.

Next, primary product *p* can be distributed to potential process technology *j'* for further processing to produce product *p'*. The distribution of primary product *p* is given by flow rate $F^{\mathrm{II}}_{pj'}$ (as shown in Equation 4.8).

$$\left(F_p\right)_s = \left(\sum_{j'=1}^{J'} F^{\mathrm{II}}_{pj'}\right)_s \qquad \forall p \forall s \qquad (4.8)$$

Additionally, flow rate $F^{\mathrm{II}}_{pj'}$ contains components *q'*. Each component *q'* has a composition $\theta_{pq'}$ and flow rate $f^{\mathrm{II}}_{q'j'}$ as shown in Equation 4.9

$$\left(f^{\mathrm{II}}_{q'j'}\right)_s = \left(\sum_{p=1}^{P} F^{\mathrm{II}}_{pj'}\theta_{pq'}\right)_s + \left(\sum_{p'=1}^{P'} F^{\mathrm{II}}_{p'j'}\theta_{p'q'}\right)_s \qquad \forall j' \forall q' \forall s \qquad (4.9)$$

where

$$\sum_{q'=1}^{Q'} \theta_{pq'} \leq 1 \qquad \forall p \qquad (4.10)$$

Components *q*' are then converted to final product *p'* with conversion $\mathrm{X}^{\mathrm{II}}_{q'j'p'}$ (Equation 4.11).

$$\left(F^{\mathrm{II}}_{j'p'}\right)_s = \left(\sum_{q'=1}^{Q'} f^{\mathrm{II}}_{q'j'}\mathrm{X}^{\mathrm{II}}_{q'j'p'}\right)_s \qquad \forall j' \forall q' \forall s \qquad (4.11)$$

The total production rate of product *p'* for all process technologies *j'* is written as;

$$\left(F^{\mathrm{Ret}}_{p'}\right)_s + \left(F_{p'}\right)_s = \left(\sum_{j'=1}^{J'} F^{\mathrm{II}}_{j'p'}\right)_s \qquad \forall p' \forall s \qquad (4.12)$$

Meanwhile, *p'* can be recycled back to technology *j* and *j'* with total flow rate $F^{\mathrm{Ret}}_{p'}$. $F^{\mathrm{Ret}}_{p'}$ can then be allocated to technology *j* and *j'* as shown;

$$\left(F_{p'}^{\mathrm{Ret}}\right)_s = \left(\sum_{j=1}^{J} F_{p'j}^{\mathrm{I}}\right)_s + \left(\sum_{j'=1}^{J'} F_{p'j'}^{\mathrm{II}}\right)_s \qquad \forall p' \forall s \qquad (4.13)$$

where $F_{p'j'}^{\mathrm{I}}$ and $F_{p'j'}^{\mathrm{II}}$ are flow rates of final product *p'* recycled to *j* and *j'* respectively.

However, in the case where a single or no process technology is required to produce the final product *p'*, biomass *i* and primary product *p* are allowed to bypass process technology *j* and *j'* via a "blank" technology (where no conversion takes place). It is important to note that the representation of final product *p'* is applicable in cases where BES outputs (e.g. steam, cooling water, etc.) are sold or exported to the end user as raw materials (e.g., in reactions). Alternatively, if BES outputs are sold or exported as utilities (e.g., for heating, cooling, power, etc.), it would be given by energy *e* which is discussed in the next sub-section.

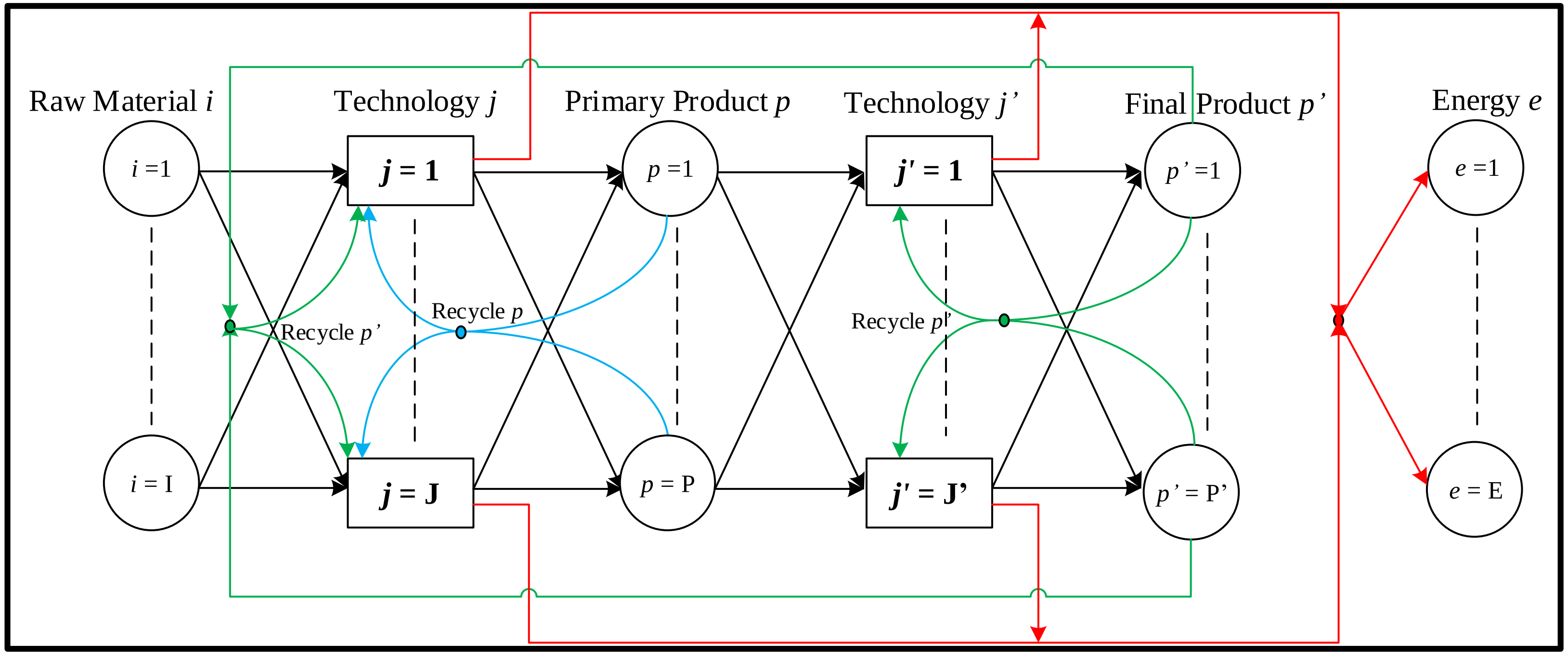

Figure 4.1: Generic Superstructure

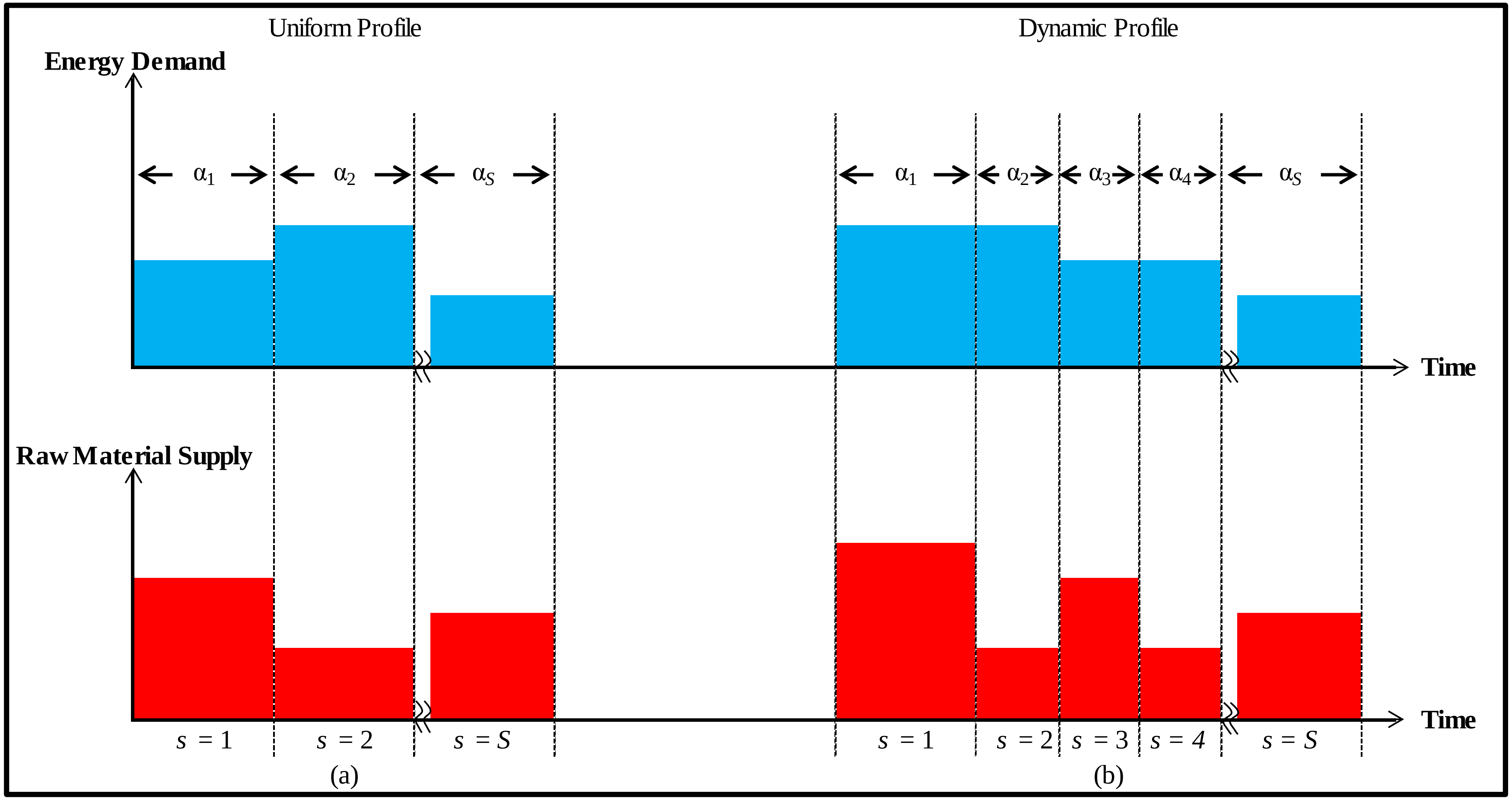

Figure 4.2: Generic Representation of Scenario *s*

4.3.2 Energy Balance

Apart from material conversions, components *q* in biomass *i* can also be converted into energy *e* via technology *j* with conversion of $\mathrm{V}^{\mathrm{I}}_{qje}$. Moreover, components *q'* in product *p* can also be converted into energy *e* via technology *j'* with conversion of $\mathrm{V}^{\mathrm{II}}_{q'j'e}$. Total energy generated by technologies *j* and *j'* is shown in Equation 4.14;

$$\left(E_e^{\mathrm{Gen}}\right)_s = \left(\sum_{q=1}^{Q}\sum_{j=1}^{J} f_{qj}^{\mathrm{I}}\mathrm{V}_{qje}^{\mathrm{I}} + \sum_{q'=1}^{Q'}\sum_{j'=1}^{J'} f_{q'j'}^{\mathrm{II}}\mathrm{V}_{q'j'e}^{\mathrm{II}}\right)_s \qquad \forall e \forall s \qquad (4.14)$$

Besides generating energy, some technologies in the BES may consume energy. The total energy consumption of BES is determined based on the energy requirement in all technologies *j* and *j'* that used to convert biomass *i* to products *p* and *p'* as well as energy *e*. The total energy consumption is showed in Equation 4.15.

$$\left(E_e^{\mathrm{Con}}\right)_s = \left(\sum_{p=1}^{P}\sum_{j=1}^{J} F_{jp}^{\mathrm{I}}\mathrm{Y}_{ejp}^{\mathrm{I}} + \sum_{p'=1}^{P'}\sum_{j'=1}^{J'} F_{j'p'}^{\mathrm{II}}\mathrm{Y}_{ej'p'}^{\mathrm{II}}\right)_s \qquad \forall e \forall s \qquad (4.15)$$

where $\mathrm{Y}^{\mathrm{I}}_{ejp}$ and $\mathrm{Y}^{\mathrm{II}}_{ejp'}$ are specific energy consumption for technologies *j* and *j'* respectively. In the case where energy generated by the BES exceeds the total energy consumption and energy demand from process or customer $\left(E_e^{\mathrm{Gen}} > E_e^{\mathrm{Con}} + E_e^{\mathrm{Demand}}\right)$, excess energy E_e^{Exp} can be sold or exported to the power grid. In contrast, import of external energy is required if the total energy consumption of the BES is more than the energy generated ($E_e^{\mathrm{Gen}} < E_e^{\mathrm{Con}} + E_e^{\mathrm{Demand}}$). The overall energy correlation for the BES can be written as

$$\left(E_e^{\text{Gen}} + E_e^{\text{Imp}}\right)_s = \left(E_e^{\text{Con}} + E_e^{\text{Demand}} + E_e^{\text{Exp}}\right)_s \qquad \forall e \forall s \qquad (4.16)$$

where E_e^{Imp} is the import of external energy into the BES.

4.3.3 Economic Aspects

The economic feasibility of the BES is analysed by determining its economic potential (*EP*). To determine *EP*, Equation 4.17 is included in the analysis.

$$EP = GP - \text{CRF} \times CAP \qquad (4.17)$$

where CRF and *CAP* represent the capital recovery factor and total capital costs of the BES respectively. The *GP* can be determined using Equation 4.18.

$$GP = \text{AOT} \times \left(\begin{array}{l} \sum_{p'=1}^{P'} F_{p'} \text{C}_{p'} + \sum_{e=1}^{E} E_e^{\text{Exp}} \text{C}_e^{\text{Exp}} - \\ \sum_{e=1}^{E} E_e^{\text{Imp}} \text{C}_e^{\text{Imp}} - \sum_{i=1}^{I} F_i^{\text{BIO}} \text{C}_i^{\text{BIO}} - \sum_{p'=1}^{P'} F_{p'} \text{C}_{p'}^{\text{Grl}} - \sum_{e=1}^{E} E_e^{\text{Exp}} \text{C}_e^{\text{Grl}} \end{array} \right) \qquad (4.18)$$

where AOT is the annual operating time, $\text{C}_{p'}$ is the selling price of products *p'*, C_e^{Exp} is the selling price of exporting excess energy *e*, C_e^{Imp} is the cost of importing external energy *e* and C_i^{BIO} is the cost of raw material (lignocellulosic biomass *i*). Meanwhile, $\text{C}_{p'}^{\text{Grl}}$ and C_e^{Grl} are cost of general expenses (e.g., start-up, manpower, installation, maintenance, etc.). Note that Equation 4.18 assumes a scenario where uncertainties do not play a role in the economic analysis. However, the solution obtained from Equation 4.18 may not necessarily be feasible in real world applications where uncertainties are present. In this respect, Equation 4.18 is modified as Equation 4.19 to incorporate the fraction of occurrence for scenario *s* (α_s).

$$GP = \sum_{s} \alpha_s \left[\text{AOT} \times \left(\begin{array}{l} \sum_{p'=1}^{P'} F_{p'} \mathrm{C}_{p'} + \sum_{e=1}^{E} E_e^{\text{Exp}} \mathrm{C}_e^{\text{Exp}} - \\ \sum_{e=1}^{E} E_e^{\text{Imp}} \mathrm{C}_e^{\text{Imp}} - \sum_{i=1}^{I} F_i^{\text{BIO}} \mathrm{C}_i^{\text{BIO}} - \sum_{p'=1}^{P'} F_{p'} \mathrm{C}_{p'}^{\text{Grl}} - \sum_{e=1}^{E} E_e^{\text{Exp}} \mathrm{C}_e^{\text{Grl}} \end{array} \right) \right] \tag{4.19}$$

Subject to:

$$\sum_{s} \alpha_s = 1 \tag{4.20}$$

With the inclusion of α_s in Equation 4.19, the economic feasibility of the BES in all *s* potential scenarios is assessed. Each fraction of occurrence represents the time fraction of which a scenario occurs. This time fraction is calculated by dividing the duration of a scenario *s* with the total duration (time horizon) considered. Thus, the sum of these fractions must equal to one as shown in Equation 4.20. Note that the duration of scenario *s* is dependent on profile of raw material supply to energy demand. Figure 4.2 (a) represents a uniform profile, whereby the supply and demand vary based on a fixed intervals. An example of this would be if supply changes on monthly basis, so does energy demand. If the raw material supply and energy demand profiles are uniform in terms of duration the time fraction of occurrence for scenario *s* can be obtained as shown in Figure 4.2(a). Dynamic characteristics of both supply and energy demand are captured based on the way the operating scenario is defined as shown in Figure 4.2 (b). In this thesis, the operating scenario *s* is determined based on the smallest interval between the supply and demand. For instance, in the case where demands vary by the hour basis while the supply varies by monthly basis, the operating scenario *s* is defined based on hourly intervals. With this consideration, optimisation constraints between scenarios can be established. Such feature is useful when dealing with seasonal variations. In practice, these fractions can be estimated subjectively based on the historical and projected information in variations of raw material supply, energy demand, product prices and etc.

On the other hand, *CAP* is determined based on the selected technologies *j* and *j'* as well as their corresponding design capacities. As shown in Equations 4.21 and 4.22, the design capacities are determined based on the maximum operating capacity among all *s* scenarios.

$$\sum_{n=1}^{N} z_{jn} \mathrm{F}_{jn}^{\mathrm{Design}} \geq \left(\sum_{p=1}^{P} F_{jp}^{\mathrm{I}} \right)_s \qquad \forall j \forall s \qquad (4.21)$$

$$\sum_{n'=1}^{N'} z_{j'n'} \mathrm{F}_{j'n'}^{\mathrm{Design}} \geq \left(\sum_{p'=1}^{P'} F_{j'p'}^{\mathrm{II}} \right)_s \qquad \forall j' \forall s \qquad (4.22)$$

where $\mathrm{F}_{jn}^{\mathrm{Design}}$ and $\mathrm{F}_{j'n'}^{\mathrm{Design}}$ represent the design capacities available for purchase for technologies *j* and *j'* respectively. Besides, z_{jn} and $z_{j'n'}$ are positive integers which represent the number of units of design capacity *n* and *n'* selected. Note that design capacities $\mathrm{F}_{jn}^{\mathrm{Design}}$ and $\mathrm{F}_{j'n'}^{\mathrm{Design}}$ can be revised according to current market availability in order to produce an up-to-date economic analysis. With these equations, chances of selecting design capacities that will result in an under designed system will be eliminated. Once the technologies are selected based on their appropriate design capacities, the total capital cost for technologies *j* and *j'* are determined via Equation 4.23

$$CAP = \sum_{j=1}^{J}\sum_{n=1}^{N} z_{jn}\mathrm{C}_{jn} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} z_{j'n'}\mathrm{C}_{j'n'} \qquad (4.23)$$

where C_{jn} and $\mathrm{C}_{j'n'}$ are capital costs of the design capacities *n* and *n'* for levels *j* and *j'* respectively.

Lastly, CRF is used to annualise capital costs by converting its present value into a stream of equal annual payments over a specified operation lifespan, t^{max} and discount rate, r. The CRF can be determined via Equation 4.24:

$$\mathrm{CRF} = \frac{\mathrm{r}(1+\mathrm{r})^{\mathrm{t}^{\max}}}{(1+\mathrm{r})^{\mathrm{t}^{\max}} - 1} \qquad (4.24)$$

In the case where operating lifespans of technologies *j* and *j'* differ from one another, Equations 4.17, 4.23 and 4.24 can be revised to give Equations 4.25 – 4.27. *ACAP* represents the total annualised capital costs.

$$EP = GP - ACAP \qquad (4.25)$$

$$ACAP = \sum_{j=1}^{J}\sum_{n=1}^{N} z_{jn}\mathrm{C}_{jn}\mathrm{CRF}_{jn} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} z_{j'n'}\mathrm{C}_{j'n'}\mathrm{CRF}_{j'n'} \qquad (4.26)$$

$$\mathrm{CRF}_{l} = \frac{\mathrm{r}(1+\mathrm{r})^{\mathrm{t}_{l}^{\max}}}{(1+\mathrm{r})^{\mathrm{t}_{l}^{\max}} - 1} \qquad \forall l, l \in jn, j'n' \qquad (4.27)$$

To illustrate this approach, a case study is presented based on palm-based biomass generated from a palm oil mill. In this case study, the BES configuration is synthesised and analysed based on the variations in pam-based biomass supply and energy demand.

4.4 Case Study

As mentioned in Section 1.2.1., palm-based biomass such as empty fruit bunches (EFBs), palm kernel shell (PKS), palm mesocarp fibre (PMF) and palm oil mill effluent (POME) contain useful amount of energy which can be recovered to meet energy demands in the industry and generate additional power for exporting to the national grid. To recover this potential energy source, a palm BES can be designed for palm oil mills (POMs). Implementing such systems would provide the industry an opportunity to turn waste products into valuable renewable energy and reduce the importation of energy from external providers (e.g., grid) (Majutek Perunding, 2014). However, due to the seasonal operations in the industry, palm-based biomass supply and energy demand tend to vary between each agricultural seasons. Such long-term variations should be taken into account as it would significantly affect the economic characteristics of the BES. In this respect, this case study presents the synthesis and design of a palm BES under seasonal variations in biomass supply and energy demand.

In this case study, it is assumed that an investor is interested to implement a new palm BES which supplies utilities such as power, low pressure steam (LPS), cooling water and chilled water to an existing POM (as shown in Figure 4.3). The raw material (palm-based biomass) for the BES is purchased from the POM at the costs shown in Table 4.1. Meanwhile, the utilities produced by the BES would be supplied to POM at the costs given in Table 4.2.

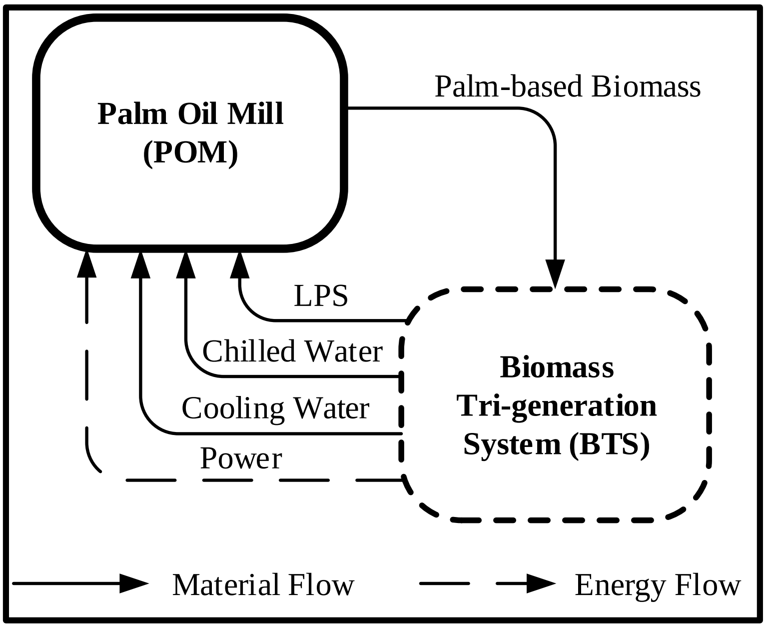

Figure 4.3: Block Diagram for Case Study

Table 4.1: Composition and Price of Palm-Based Biomass for Cases 1 – 2

Raw Materials *i*	Component *q*	Composition θ_{iq} (%)	Cost, C_i^{BIO} (US$/tonne)
EFB	Cellulose	13	6
	Hemi-Cellulose	12	
	Lignin	8	
	Water	65	
	Ash	2	
PMF	Cellulose	21	22
	Hemi-Cellulose	19	
	Lignin	15	
	Water	40	
	Ash	5	
PKS	Cellulose	16	50
	Hemi-Cellulose	17	
	Lignin	39	
	Water	23	
	Ash	4	

Table 4.2: Cost of Utilities

Utility Sales	Base Unit	Cost (US$/Unit)
Electricity to the grid, C_e^{Exp}	kWh	0.095
Electricity to POM, C_e^{Exp}	kWh	0.09
Electricity from the grid, C_e^{Imp}	kWh	0.12
LPS to POM, $C_{p'}$	tonne	25.00
Cooling Water to POM, $C_{p'}$	tonne	0.09
Chilled Water to POM, $C_{p'}$	tonne	0.62

Apart from that, this case study assumes that the existing POM has the similar behaviour of a typical POM presented by Kasivisvanathan et al. (2012). As illustrated in Figure 4.4, the input-output model shows the overall input and output flow rates of the POM normalised to the rate of crude palm oil (CPO) produced. As shown, the amount of biomass generated by the POM is dependent on its CPO production.

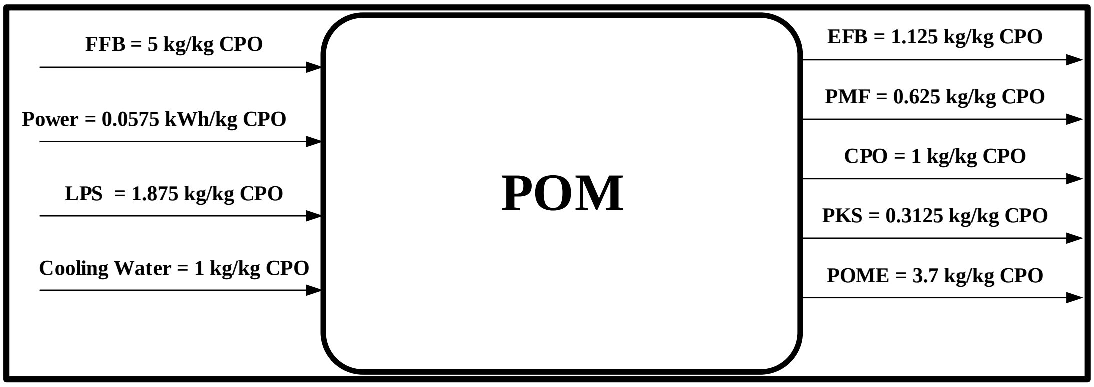

Figure 4.4: Normalised Production for POM (Kasivisvanathan et al., 2012)

In the Malaysian palm oil industry, total CPO productions tend to vary between agricultural seasons, as shown in Figure 4.5. Based on national statistics (Malaysian Palm Oil Board, 2014) (Figure 4.5), the production of CPO can be divided into three seasons (low season, mid-season and high season). In this case study, total CPO productions less than 1,600,000 tonnes/yr is taken as the low season. Meanwhile, total CPO productions fall in between 1,600,000 and 1,800,000 tonnes/yr is taken as the mid-season; total CPO productions higher than 1,800,000 tonnes/yr are then taken as high season. Due to the seasonal operation, it is foreseen that the demand from the POM would vary according to its seasonal period in a calendar year. It is imperative that BES investor give special attention to the variation as energy demand patterns significantly affect the economic characteristics of the BES. As such, the fraction of occurrence for each season is taken into consideration to synthesise a BES. The fraction of occurrence can be estimated based on the number of months in a calendar year in which the CPO production falls in the low, mid and high season (as shown in Table 4.3). It is noted that the seasons and corresponding fraction are calculated based on the actual CPO production of the Malaysian palm oil industry for 2013 (as shown in Figure 4.5). It is worth mentioning that more realistic values may be calculated based on the long term average. The energy demand for each season is typically specified by the client. In this case study, it is assumed that the client determines POM seasonal energy demands using the input-output model as shown in Figure 4.4. For the low, mid and high seasons, the CPO production from the POM studied in this case study, is assumed to be 11000 kg/h, 13000 kg/h and 15000 kg/h respectively. Based on these CPO flow rates, the seasonal utility demand and palm-based biomass generated from the POM are summarised in Tables 4.4 and 4.5. As shown in Tables 4.4 and 4.5, each season has uniform biomass supply and energy demand profiles. In this respect, each season of biomass supply and energy demand is represented by a fraction of occurrence.

Table 4.3: Fraction of Occurrence for Low, Mid and High Seasons

Season	Occurrence	Fraction of Occurrence
Low	Less than 1,600,000 tonnes	$\alpha_L = 0.417$
Mid	Between 1,600,000 to 1,800,000 tonnes	$\alpha_M = 0.333$
High	More than 1,800,000 tonnes	$\alpha_H = 0.250$

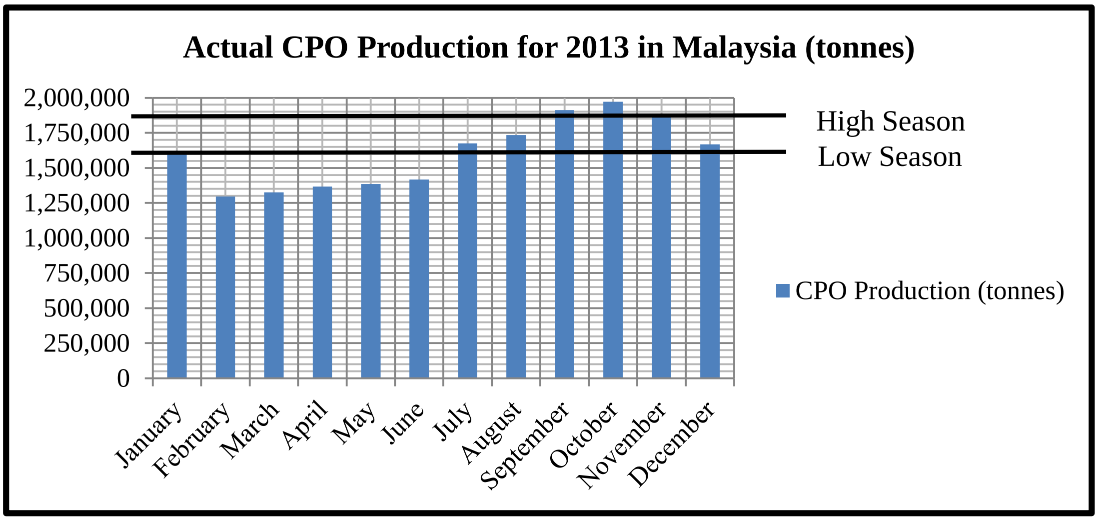

Figure 4.5: Total CPO Production in Malaysia for 2013

Table 4.4: Utility Demand of POM

Utility	Unit	Low Season	Mid Season	High Season
Electricity	kWh	632.5	747.5	862.5
LPS	kg/h	20,625.00	24,375.00	28,125.00
Cooling Water	kg/h	11,000.00	13,000.00	15,000.00
Chilled Water*	kg/h	1,000.00	1,000.00	1,000.00

*Constant throughout the year as it is for office air conditioning purposes

Table 4.5: Palm-Based Biomass Availability

Available Raw Material Supply	Low Season (kg/h)	Mid Season (kg/h)	High Season (kg/h)
EFB	12,375.00	1,4625.00	16,875.00
PMF	6,875.00	8,125.00	9,375.00
PKS	3,437.5.00	4,062.50	4,687.50
POME	40,700.00	48,100.00	55,500.00

A superstructure is developed to include all possible technologies and configurations (as shown in Figure 4.6). Note that although only one unit is shown in the superstructure, it is possible to have several pieces in the case where units with smaller design capacities are selected (as described in Equations 4.21 and 4.22). All these alternatives are then mathematically modelled (according to Equations 4.1 – 4.17 and 4.19 – 4.24), allowing quantitative analysis and optimisation. A list of available design capacities considered in this case study is provided in Table 4.6. Discrete sizes are considered in this case study as available equipment sizes are often fixed by the vendor. For each respective design capacity, the capital costs are estimated using correlations presented by Peters et al. (2002). In addition, detailed conversion data, mass and energy balance calculations for this case study are also provided in Table 4.7.

To demonstrate the proposed work, three cases are taken into consideration. In the first case, the optimisation objective is to synthesise a BES with the maximum economic performance. As for the second case, the optimisation objective is to synthesise a BES with the maximum economic performance subject to a maximum capital investment of US$ 3,703,704 (RM 12,000,000, whereby 1 US$ = RM 3.24). Similar to Case 1, the optimisation objective of Case 3 is to synthesise a BES configuration with maximum economic performance. However, Case 3 considers biomass of different quality as compared to Case 1 (shown in Table 4.8). Table 4.9 shows the economic parameters that considered in this case study. The MILP model for all cases are solved via LINGO v14 (Branch and Bound Solver) (LINDO Systems Inc., 2011) using a Dell Vostro 3400 with Intel Core i5 (2.40GHz) and 4GB DDR3 RAM. Details of the models (e.g., codes, result scripts, CPU time, variables, integers, etc.) for all three cases are included in Section A.1 of the Appendices.

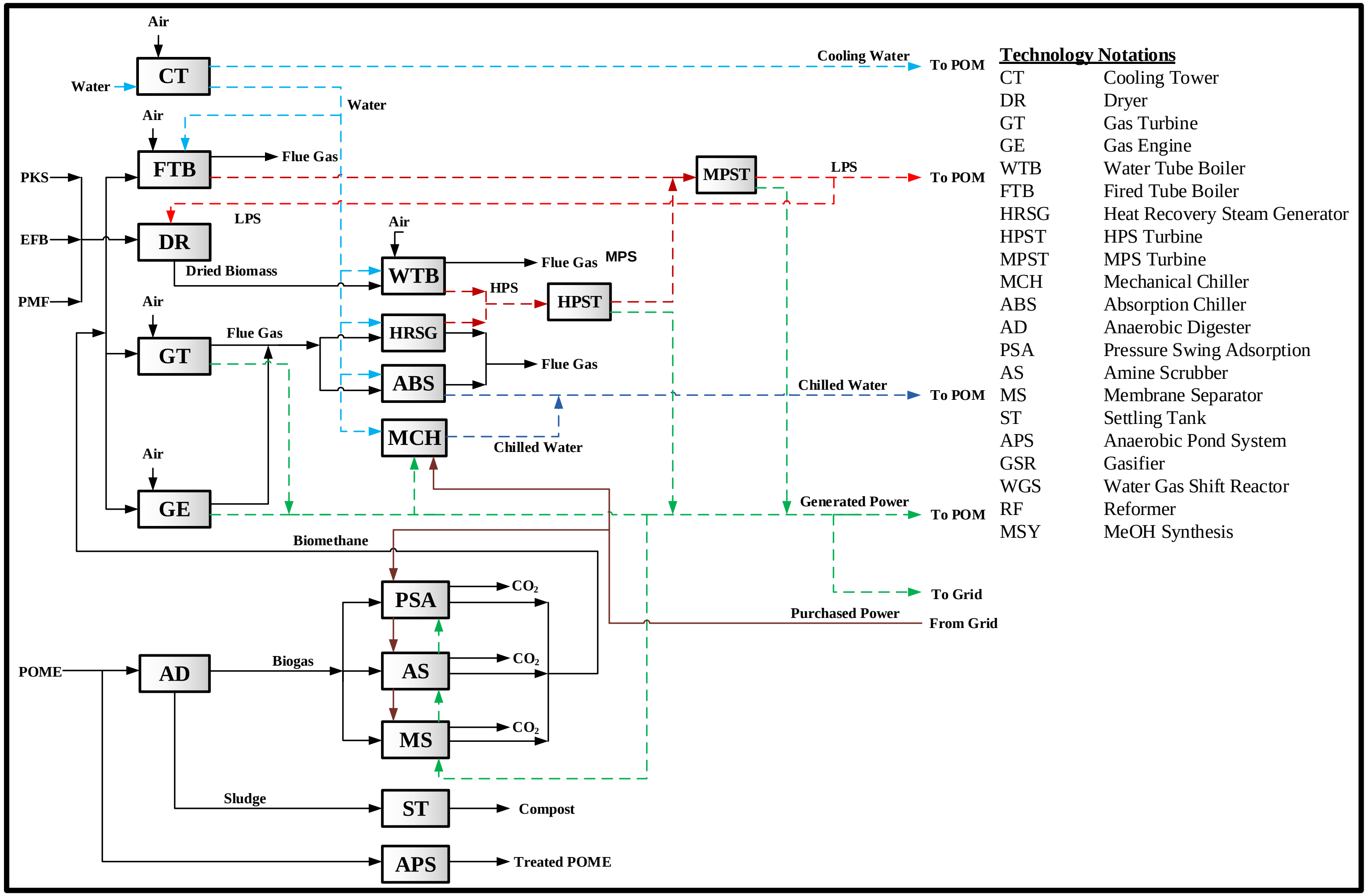

Figure 4.6: Superstructure for Palm BES Case Study

Table 4.6: Capital Costs for each Technology and Available Design Capacity

Technology	Design Capacity	Capital Costs (US$)
WT-Boiler	84 kg/s	3,841,076
	70 kg/s	3,353,655
	40 kg/s	2,211,185
FT-Boiler	12 kg/s	902,498
	10 kg/s	787,974
	6 kg/s	538,753
HPS Turbine	5,000 kW	165,401
	500 kW	122,380
	250 kW	90,549
MPS Turbine	500 kW	122,380
	250 kW	90,549
	200 kW	82,180
Gas Turbine	5,000 kW	274,778
	500 kW	179,647
	250 kW	117,451
Internal Combustion Engine	315 kW	77,077
	400 kW	93,828
Dryer	40,000 kg/h	720,000
	25,000 kg/h	450,000
	10,000 kg/h	180,000
Amine Scrubbing	700 kg/h	3,166,744
	500 kg/h	2,261,960
	200 kg/h	904,784
PSA	500 kg/h	1,546,605
	200 kg/h	618,642
	100 kg/h	309,321
Membrane Separation	180 kg/h	501,111
	100 kg/h	278,395
	70 kg/h	194,877

Table 4.6: (Continued)

Heat Recovery Steam Generator	12 kg/s	902,498
	40 kg/s	2,211,185
Absorption Chiller	250 kW	42,518
	300 kW	48,926
	350 kW	55,092
Mechanical Chiller	250 kW	42,518
	300 kW	48,926
	350 kW	55,092
Cooling Tower	50 kg/s	25,867
	30 kg/s	17,762
	25 kg/s	15,532
Anaerobic Digester	Based on Available flow	11.9/(kg/h) POME

Table 4.7: Conversions for Technologies Considered in Cases 1 – 3

Technology	Conversion	Inlet	Product/ By-Product	References
Water Tube Boiler	0.5556 kg H_2O/kg Cellulose[a] 0.5556 kg H_2O/kg Hemi-Cellulose[a] 1.674 kg H_2O/kg Lignin[a] 1.63 kg CO_2/kg Cellulose[a] 1.63 kg CO_2/kg Hemi-Cellulose[a] 3.9 kg CO_2/kg Lignin[a] Efficiency = 0.55 1.19 kg O_2/kg Cellulose[a] 1.19 kg O_2/kg Hemi-Cellulose[a] 4.13 kg O_2/kg Lignin[a] Steam Enthalpy (30 bar, 350^{0}C) = 2858 kJ/kg Water Enthalpy (1.01 bar, 30^{0}C) = 104.92 kJ/kg Heating Value (Cellulose) = 17,000 kJ/kg Cellulose Heating Value (Hemi-cellulose) = 16,000 kJ/kg Hemi-Cellulose Heating Value (Lignin) = 25,000 kJ/kg Lignin	Water (30^{0}C) Dried Palm Biomass Air	HPS (30 bar, 350^{0}C)	(Rogers and Mayhew, 1964), (BISYPLAN, 2012), (Murphy and Masters, 1978)

Table 4.7: (Continued)

Fired Tube Boiler	2.25 kg H_2O/kg Bio-methane[a] 2.75 kg CO_2/kg Bio-methane[a] 4 kg O_2/kg Bio-methane[a] Efficiency = 0.60 Steam Enthalpy (20 bar, 284^{0}C) = 2,736 kJ/kg Water Enthalpy (1.01 bar, 30^{0}C) = 104.92 kJ/kg Heating Value (Bio-methane) = 22,000 kJ/kg Bio-methane	Water (30^{0}C) Bio-methane Air	MPS (20 bar, 284^{0}C)	(Rogers and Mayhew, 1964), (The Engineering ToolBox, 2013)
HPS Turbine	Steam Enthalpy (30 bar, 350^{0}C) = 2,858 kJ/kg Steam Enthalpy (20 bar, 284^{0}C) = 2,736 kJ/kg Efficiency = 0.98	HPS (30 bar, 350^{0}C)	MPS (20 bar, 284^{0}C) Electricity	(Rogers and Mayhew, 1964)
MPS Turbine	Steam Enthalpy (20 bar, 284^{0}C) = 2,736 kJ/kg Steam Enthalpy (3 bar, 134^{0}C) = 2,707 kJ/kg Efficiency = 0.98	MPS (20 bar)	LPS (3 bar, 134^{0}C) Electricity	(Rogers and Mayhew, 1964)

Table 4.7: (Continued)

Gas Turbine	2.25 kg H_2O/kg Bio-methane[a] 2.75 kg CO_2/kg Bio-methane[a] 4 kg O_2/kg Bio-methane[a] Flue Gas Enthalpy (16 bar)[b] = -1,142 kJ/kg Flue Gas Enthalpy (1.01 bar)[b] = 41.09 kJ/kg Efficiency = 0.60	Bio-methane Air	Flue Gas Electricity	
Internal Combustion Engine	2.25 kg H_2O/kg Bio-methane[a] 2.75 kg CO_2/kg Bio-methane[a] 4 kg O_2/kg Bio-methane[a] Heating Value (Bio-methane) = 22,000 kJ/kg Bio-methane Efficiency = 0.20 Operating Conditions: 16 bar, 600^{0}C	Bio-methane Air	Flue Gas Electricity	(The Engineering ToolBox, 2013)
Dryer	Outlet Moisture Content (wt%) = 10	Wet Palm Biomass	Dried Palm Biomass	
Amine Scrubbing	0.9994 kg Bio-methane/ kg Raw Bio-methane 0.998 kg CO_2/ kg Raw CO_2 Power Required = 0.14 kWh/kg Biogas	Bio-methane (65wt%) CO_2 (35wt%)	Bio-methane (97wt%) CO_2 (98wt%)	(Bauer et al., 2013)

Table 4.7: (Continued)

Pressure Swing Adsorption	0.98 kg CO_2/ kg Raw Bio-methane 0.98 kg CO_2/ kg Raw CO_2 Power Required = 0.3 kWh/kg Biogas	Bio-methane (65wt%) CO_2 (35wt%)	Bio-methane (97wt%) CO_2 (98wt%)	(Bauer et al., 2013)
Membrane Separation	0.99 kg Bio-methane/ kg Raw Bio-methane 0.98 kg CO_2/ kg Raw CO_2 Power Required = 0.3 kWh/kg Biogas	Bio-methane (65wt%) CO_2 (35wt%)	Bio-methane (97wt%) CO_2 (98wt%)	(Bauer et al., 2013)
Heat Recovery Steam Generator	Flue Gas Enthalpy = 2,076.29 kJ/kg Efficiency = 0.35 Steam Enthalpy (30 bar, 350^{0}C) = 2,858 kJ/kg Water Enthalpy (1.01 bar, 30^{0}C) = 104.92 kJ/kg	Water (30^{0}C) Flue Gas	HPS (30 bar, 350^{0}C)	(Rogers and Mayhew, 1964)
Absorption Chiller	COP = 0.7 Output kW/ Input kW Flue Gas Enthalpy[b] = 799.12 kJ/kg Cooling Water = 7.247 kg/kWh Chilled Water = 0.00722 kg/kWh	Cool Water (30^{0}C) Flue Gas (600^{o}C)	Chilled Water (7^{0}C) Flue Gas (30^{o}C)	(Chartered Institution of Building Services Engineers, 2012), (Air-Conditioning Heating & Refrigeration Institute, 2000), (Air-Conditioning Heating & Refrigeration Institute, 2000)

Table 4.7: (Continued)

Mechanical Chiller	COP = 6.1 Output kW/ Input kW Cooling Water = 7.247 kg/kWh Chilled Water = 0.00722 kg/kWh	Cool Water (30^0C) Electricity	Chilled Water (7^0C)	(Hondeman, 2000)
Cooling Tower	Air Required = 20.1 kg/kWh Cooling Load = 42 kJ/kg Water	Hot Water (40^0C) Air	Cool Water (30^0C)	
Anaerobic Digester	Bio-methane = 0.184 kg/kg COD CO_2 = 0.0992 kg/kg COD COD = 50,000 mg/L POME Density = 1,600 kg/m^3 Sludge = 0.06 kg/kg POME	POME	Bio-methane (65wt%) CO_2 (35wt%)	(Chin et al., 2013)

[a]Based on stoichiometric balance for complete combustion reaction; [b]Based on Aspen Hysys Simulation.

Table 4.8: Composition and Price of Palm-Based Biomass for Case 3

Raw Materials *i*	**Component *q***	**Composition θ_{iq} (%)**	**Cost, C_i^{BIO} (US$/tonne)**
EFB	Cellulose	10	6
	Hemi-Cellulose	11	
	Lignin	5	
	Water	72	
	Ash	2	
PMF	Cellulose	21	22
	Hemi-Cellulose	19	
	Lignin	15	
	Water	40	
	Ash	5	
PKS	Cellulose	17	50
	Hemi-Cellulose	18	
	Lignin	41	
	Water	21	
	Ash	3	

Table 4.9: Economic Parameters for Case 1 and 2

Operational Hours, AOT	5,000/yr
*Operation Lifespan, t^{max}	15 yr
CRF	0.13/yr
*Discount Rate, r	10%
Currency Conversion Rate	1 US$ (RM 3.24)

*t^{max} and r are assumed to be the same for all technologies considered

Case 1: To synthesise a BES with maximum economic performance while meeting the POM demand shown in Table 4.4, the developed model is optimised based on Equation 4.28 subject to Equations 4.1 – 4.17 and 4.19 – 4.24.

$$\text{Maximise } EP \tag{4.28}$$

The optimised results for this case are summarised in Table 4.10. Note that the synthesised configuration of BES is shown in Figure 4.7. As shown in Table 4.10, the *GP* is found as US$ 2,736,173 (RM 8,865,200) per year over its operational lifespan of 15 years. In addition, the total *CAP* of the system is found as US$ 5,884,475 (RM 19,065,700) with the corresponding design capacities for the technologies shown in Table 4.11. Note also that the simple payback period of the synthesised BES is determined as 2.15 years.

Case 2: In this case, the investor would unlikely implement a BES if the required capital cost is more than US$ 3,703,704 (RM 12,000,000). Thus, *EP* is maximised (Equation 4.28) subject to additional constraints as shown in Equation 4.29 along with other constraints from Case 1.

$$CAP \leq \text{US\$ } 3{,}703{,}704 \qquad (4.29)$$

The configuration synthesised for Case 2 is shown in Figure 4.8. Based on the optimisation results in Table 4.10, the *GP* is found as US$ 2,152,335 (RM 6,973,566) per year while the *CAP* is found to be US$ 3,698,886 (RM 11,984,390). Table 4.11 shows the corresponding design capacities of the selected technologies. Meanwhile, the payback period is determined as 1.72 years.

Case 3: In this case, different quality biomass is considered to analyse its impact on economic and design related decisions. As shown in Table 4.8, biomasses EFB and PKS quality are compared to Case 1. Thus, *EP* is maximised (Equation 4.28) subject to constraints from Case 1.

The configuration synthesised for Case 3 is shown in Figure 4.9. Based on the optimisation results in Table 4.10, the *GP* and *CAP* are determined as US$ 2,324,051 (RM 7,529,925) per year and US$ 5,672,645 (RM 18,379,370) respectively. Table 4.11 shows the corresponding design capacities of the selected technologies. The payback period is determined as 2.44 years.

Table 4.10: Model Output for Cases 1 – 3

	Case 1	**Case 2**	**Case 3**
Average Power Generated (kW)	2,503.5	1,452.0	2,438.6
Average Power to Grid (kW)	1,694.4	723.7	1,629.5
Average Power to Palm Oil Mill (kW)	728.3	728.3	728.3
Average Power from Grid (kW)	0.0	0.0	0.0
GP (US$/yr)	2,736,173	2,152,335	2,324,051
CAP (US$)	5,884,475	3,698,886	5,672,645
Payback Period (yr)	2.15	1.72	2.44

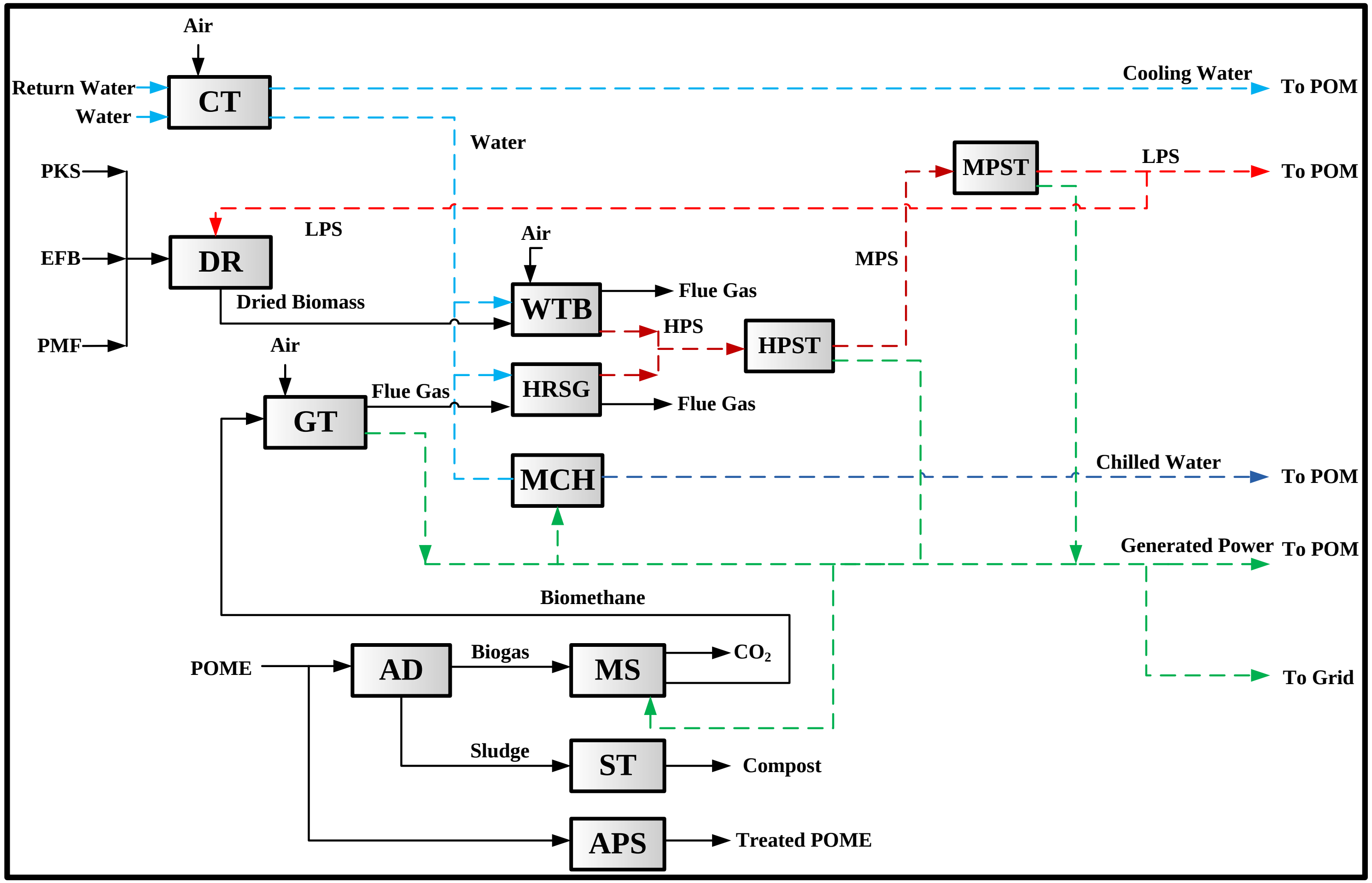

Figure 4.7: Synthesised Configuration of Palm BES in Case 1

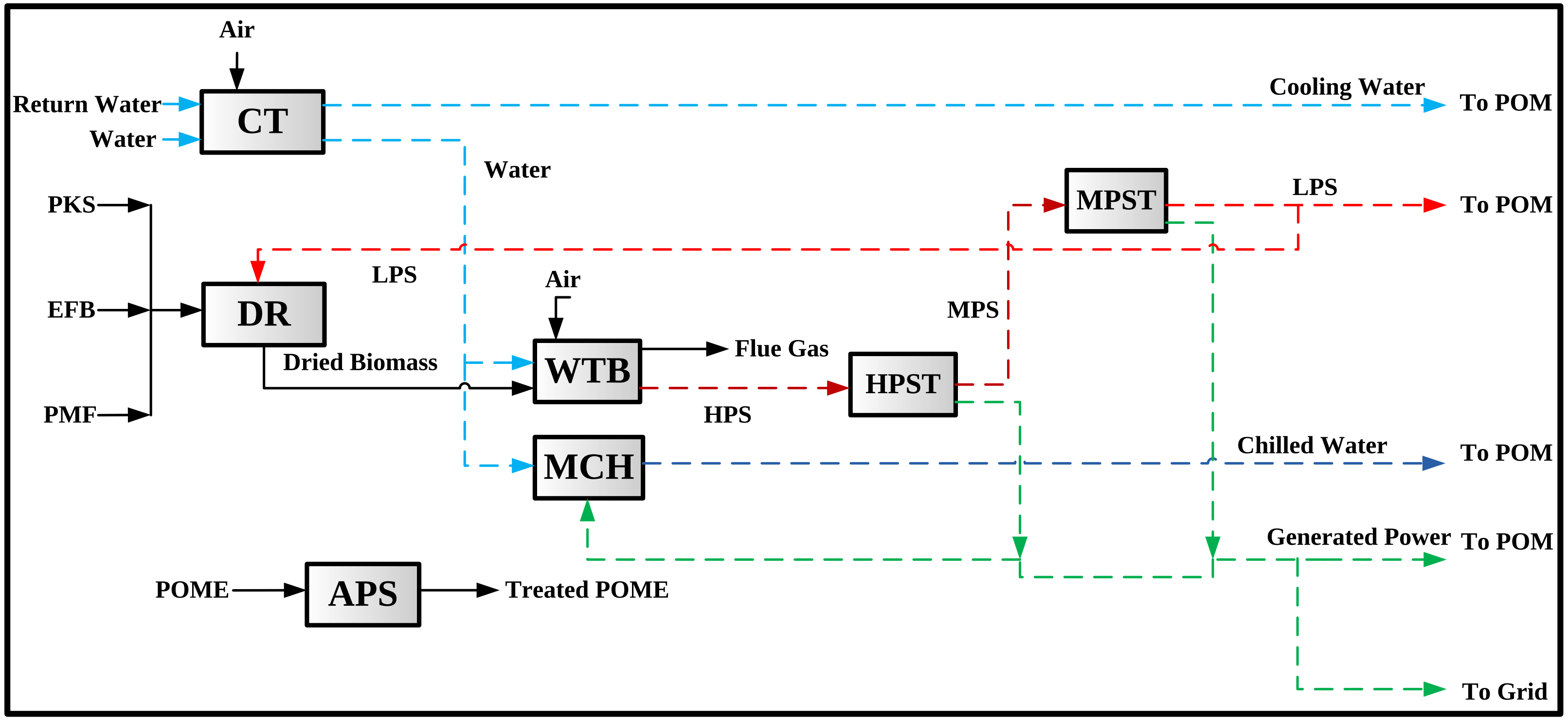

Figure 4.8: Synthesised Configuration of Palm BES in Case 2

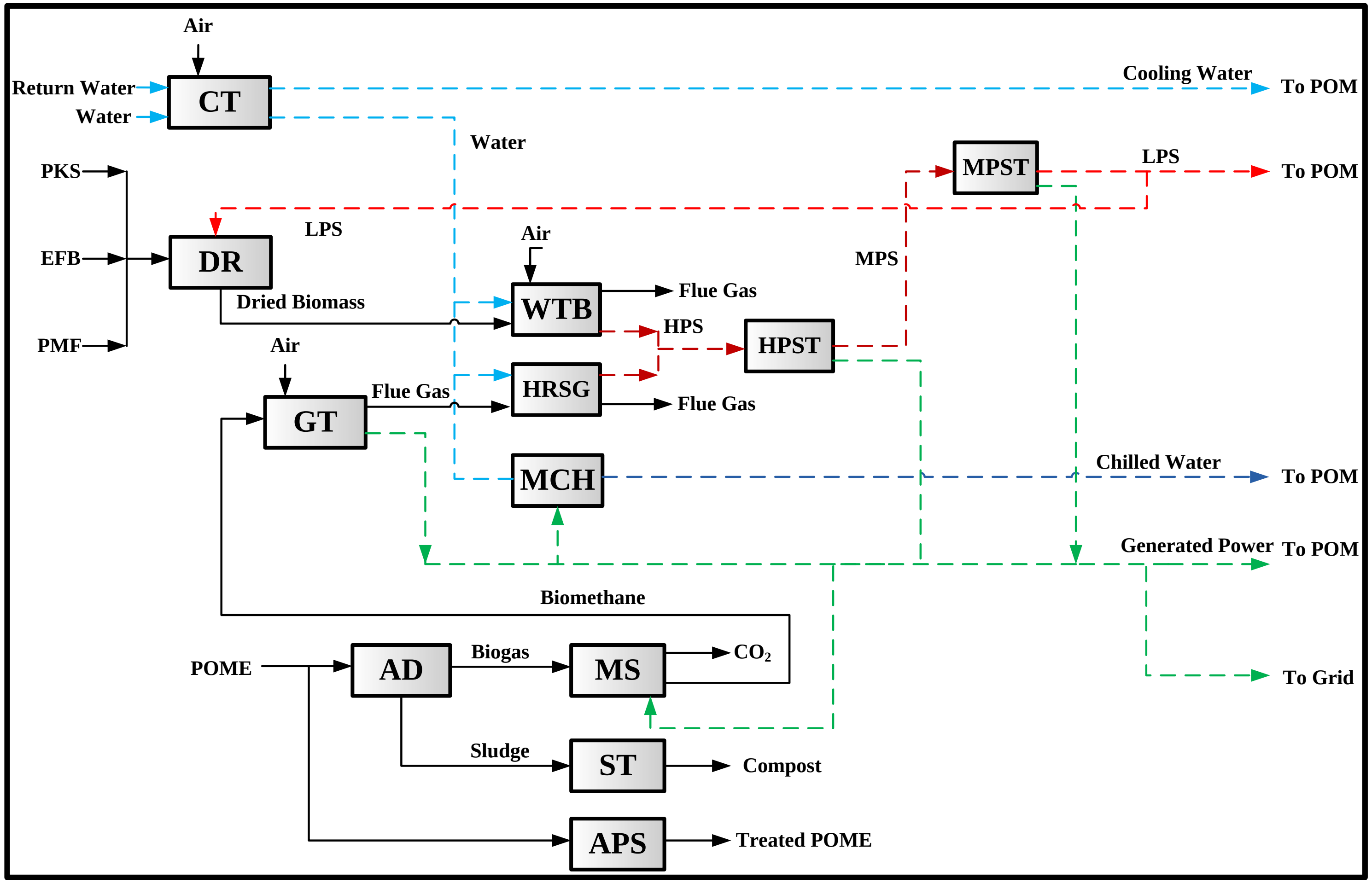

Figure 4.9: Synthesised Configuration of Palm BES in Case 3

Table 4.11: Chosen Technologies for Cases 1 – 3

Technology	Design Capacity	Case 1	Case 2	Case 3
WT-Boiler	40 kg/s	1	1	1
HPS Turbine	1,000 kW	1	1	1
	500 kW	1	1	0
	250 kW	0	0	1
MPS Turbine	500 kW	1	1	1
Gas Turbine	1,000 kW	1	0	1
	250 kW	1	0	1
Dryer	10,000 kg/h	2	2	1
Membrane Separation	180 kg/h	1	0	1
	70 kg/h	2	0	2
Heat Recovery Steam Generator	12 kg/s	1	0	1
Mechanical Chiller	250 kW	1	1	1
Cooling Tower	25 kg/s	1	1	1
Anaerobic Digester	Based on Available flow	1	0	1
Anaerobic Pond	Based on Available flow	0	1	0
Total Units		**15**	**8**	**14**

4.5 Results Analysis

As mentioned previously, the optimisation results for Cases 1 – 3 are summarised in Tables 4.10 – 4.13, Figures 4.7 – 4.9. As shown in Table 4.10, the synthesised BES configuration in Case 1 yielded a higher *GP* as compared to Case 2 and 3. Table 4.11 summarises the design capacities chosen for all BES configurations (Cases 1 – 3) based on their market availability. In addition, the number of technologies chosen for the BES configuration in Case 2 is lesser than that of Case 1 and 3. This is evident as the number of units selected for Cases 1, 2 and 3 are 15, 7 and 14 respectively. This is because Case 1 utilised POME to generate and sell the additional power to the grid. In Case 1, an anaerobic digester is selected to convert POME into biogas, followed by membrane separation units to purify the biogas to produce bio-methane. Gas turbines are selected to utilise bio-methane to produce additional power and a heat recovery steam generator (HRSG) to generate steam. In Case 2, it is noted that POME was not utilised for producing biogas but instead was treated in an anaerobic pond system due to the constraint imposed on the *CAP*. Thus, surplus power generated by the BES configuration in Case 2 is much lower than in Case 1. As for Case 3, the amount of biomass utilised is lesser than in Case 1. As such, only one dryer was chosen in Case 3 instead of two dryers as shown in Case 1. This shows that the different biomass quality introduced in Case 3 has an impact on the number of technologies chosen and subsequently the *GP* of the BES.

On the other hand, Table 4.12 shows that the amount of EFB, PMF and PKS biomasses utilised in Case 2 are higher than in Case 1 and 3. Since POME is utilised to generate power in Case 1, less amount of EFB, PMF and PKS would be required to achieve maximum *GP*. In contrast, Case 2 utilised more of EFB, PMF and PKS biomasses to compensate for not generating power from POME. Besides that, Case 3 utilised much higher amount of PKS biomass than in Case 1 and 2 due to the low quality EFB biomass considered. Despite such difference in all three cases, it is noted the available palm-based biomass supply in each season was sufficient for the BES to be energy self-sustained and to meet the POM demands (shown in Table 4.13).

Table 4.12: Available and Consumed Palm-Based Biomass for Cases 1 – 3

	Biomass	Low Season		Mid Season		High Season	
		Available (kg/h)	Consumed (kg/h)	Available (kg/h)	Consumed (kg/h)	Available (kg/h)	Consumed (kg/h)
Case 1	EFB	12,375.00	12,375.00	14,625.00	14,625.00	16,875.00	16,875.0
	PMF	68,75.00	6,875.00	8,125.00	8,125.00	9,375.00	9,375.0
	PKS	3,437.50	132.40	4,062.50	156.50	4,687.50	180.6
	POME	40,700.00	40,700.00	48,100.00	48,100.00	55,500.00	55,500.0
Case 2	EFB	12,375.00	12,375.00	14,625.00	14,625.00	16,875.00	16,875.0
	PMF	6,875.00	6,875.00	8,125.00	8,125.00	9,375.00	9,375.0
	PKS	3,437.50	563.40	4,062.50	665.90	4,687.50	768.3
	POME	40,700.00	0.00	48,100.00	0.00	55,500.00	0.0
Case 3	EFB	12,375.00	10,781.30	14,625.00	10,074.60	16,875.00	8,574.1
	PMF	6,875.00	6,875.00	8,125.00	8,125.00	9,375.00	9,375.0
	PKS	3,437.50	17,56.70	4,062.50	2,275.40	4,687.50	28,53.3
	POME	40,700.00	40,700.00	48,100.00	48,100.00	55,500.00	55,500.0

Table 4.13: Power Distribution for Cases 1 – 3

Season	Power Distribution	Case 1 (kW)	Case 2 (kW)	Case 3 (kW)
Low	To Mill	632.5	632.5	632.5
	Internally	70.2	0.0	70.2
	To Grid	1,471.5	628.5	1,474.4
Mid	To Mill	747.5	747.5	747.5
	Internally	83.0	0.0	83.0
	To Grid	1,739.0	742.8	1,667.3
High	To Mill	862.5	862.5	862.5
	Internally	95.7	0.0	95.7
	To Grid	2,006.6	857.0	1,837.8

4.6 Summary

In Chapter 4, a systematic multi-period optimisation approach was presented to synthesise a BES configuration with maximum economic performance considering seasonal variations in biomass supply and energy demand. Besides determining the BES configuration, selection of design capacities based on the available size in the market is also performed simultaneously. To illustrate the proposed approach, a palm-based biomass case study was solved. In the case study, three different cases were considered. In Case 1, the BES configuration is synthesised based on three seasons with different biomass supply and energy demand from POM. In Case 2, the BES configuration is synthesised with a constraint imposed on the capital investment. As for Case 3, biomass of lower quality (than in Case 1) was considered. Based on the results obtained for all three cases, it is noted the available biomass is sufficient for use in the BES. It is also noted that different design configurations were chosen for each case. In Chapter 5, reliability of equipment is incorporated to consider short-term uncertainties such as equipment failure in the synthesis of a reliable BES.

CHAPTER 5

SYNTHESIS AND OPTIMISATION OF BIOMASS-BASED ENERGY SYSTEMS WITH RELIABILITY ASPECTS

5.1 Introduction

In the previous chapter, a systematic approach was developed to consider uncertainties in biomass supply and energy demand for the synthesis of a biomass-based energy system (BES). However, considering such uncertainties alone may not be sufficient to yield a reliable BES. This is because interdependencies among process units in tri-generation systems can lead to vulnerability to cascading failures. Process units may become non-functional during the course of operations as a result of planned or unplanned stoppages. In Chapter 5, a systematic approach for the grassroots design of a reliable BES considering equipment redundancy is presented. *k*-out-of-*m* system modelling and the principles of chance-constrained programming (CCP) are used to develop a multi-period optimisation model for a generic BES. Two case studies are then solved to illustrate this modelling approach.

5.2 Problem Statement

A generic representation of the grassroots synthesis problem is shown in Figures 4.1 – 4.2 and 5.1. The grassroots design problem addressed is stated as follows: Given a biomass supply and energy demand scenario *s*, biomass *i* with flow rate $\left(F_i^{\mathrm{BIO}}\right)$ and its composition $q \in Q$ (e.g., lignin, cellulose, and hemi-cellulose), can be converted to primary product $p \in P$ through technologies $j \in J$. Primary product p and its composition $q' \in Q'$ can be further converted to final products $p' \in P'$ via technologies $j' \in J'$. Besides producing primary and final products p and p', process technologies j and j' can also generate energy $e \in E$.

In Chapter 5, the objective is to develop a systematic approach for the grassroots design of a reliable BES configuration with maximum economic performance, considering multiple supply and demand scenarios, $s \in S$. In each considered scenario, various design capacities $n \in N$ and $n' \in N'$ are available for selection within process technologies j and j' respectively. Based on the aforementioned problem, a mathematical model is formulated via *k*-out-of-*m* system modelling and chance-constrained programming (CCP) within a multi-period optimisation framework, where each scenario s is assigned a fraction of occurrence, α_s.

The following section further explains parameters and variables involved in the mathematical model developed for Chapter 5. The equations formulated in the mathematical model are clearly presented and described methodically to address the grassroots BES design problem.

5.3 Mathematical Optimisation Formulation

Based on Figure 4.1, the following Sections 5.3.1 – 5.3.3 present a detailed formulation of the proposed multi-period optimisation model.

5.3.1 Material and Energy Balance

Similar to Chapter 4, multiple raw material supply and energy demand scenarios are considered in Chapter 5 (based on Figures 4.1 – 4.2). In this respect, the material energy balance formulations shown in Chapter 4, i.e., Equations 4.1 – 4.14 respectively, are used in Chapter 5.

5.3.2 Economic Aspects

The extension to the work in Chapter 4 begins from Section 5.3.2. As shown in Equation 5.1, the economic performance formulation in Equation 4.15 is modified to introduce a new variable denoted as *MAC*. In Equation 5.1, *MAC* represents the total maintenance costs of the BES while *GP*, CRF and *CAP* are the gross profit, capital recovery factor and total capital costs respectively.

$$EP = GP - \mathrm{CRF} \times CAP - MAC \tag{5.1}$$

The *GP* can be determined using Equation 5.2, where AOT is the annual operating time, $\mathrm{C}_{p'}$ is the selling price of products *p'*, $\mathrm{C}_{e}^{\mathrm{Exp}}$ is the selling price of exporting excess energy *e*, $\mathrm{C}_e^{\mathrm{Imp}}$ is the cost of importing external energy *e*, $\mathrm{C}_i^{\mathrm{BIO}}$ is the cost of raw material (lignocellulosic biomass *i*) and α_s is the fraction of occurrence for scenario *s* respectively.

$$GP = \sum_s \alpha_s \left[\mathrm{AOT} \times \left(\sum_{p'=1}^{P'} F_{p'} \mathrm{C}_{p'} + \sum_{e=1}^{E} E_e^{\mathrm{Exp}} \mathrm{C}_e^{\mathrm{Exp}} - \sum_{e=1}^{E} E_e^{\mathrm{Imp}} \mathrm{C}_e^{\mathrm{Imp}} - \sum_{i=1}^{I} F_i^{\mathrm{BIO}} \mathrm{C}_i^{\mathrm{BIO}} \right)_s \right] \tag{5.2}$$

Subject to:

$$\sum_s \alpha_s = 1 \tag{5.3}$$

With the inclusion of α_s in Equation 5.3, the economic feasibility of the BES in all *s* potential scenarios is evaluated via multi-period optimisation. In multi-period optimisation, each fraction of occurrence represents the time fraction of which a scenario occurs. This time fraction is calculated by dividing the duration of a scenario *s* with the total duration (time horizon) considered. Thus, the sum of these fractions must equal to one as shown in Equation 5.3. Note that the duration of scenario *s* is dependent on the raw material supply and energy demand profiles. For instance, if the raw material supply and energy demand profiles are uniform in terms of duration (e.g., hourly, weekly, monthly basis, etc.) the time fraction of occurrence for scenario *s* can be obtained as shown in Figure 4.2(a). As for dynamic profiles where supply and demand profiles are not uniform, the duration of scenario *s* can be broken down to smaller intervals and obtained as shown in Figure 4.2(b). With this consideration, optimisation constraints between scenarios can be established. Such feature is useful when dealing with seasonal variations. In practice, these fractions can often be estimated subjectively based on the historical and projected information on variations of raw material supply, energy demand, product prices, etc.

On the other hand, *CAP* is determined based on the selected design capacities for technologies *j* and *j'* respectively (Equation 5.4). As shown, Equation 5.4 is a modified form of Equation 4.21. In Equation 5.4, C_{jn} and $C_{j'n'}$ represent the capital cost for process technology *j* and *j'* with design capacities *n* and *n'* respectively. Meanwhile, m_{jn} and $m_{j'n'}$ are positive integers that represent the total number of installed units of design capacity *n* and *n'* in *j* and *j'* respectively.

$$CAP = \sum_{j=1}^{J}\sum_{n=1}^{N} m_{jn} C_{jn} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} m_{j'n'} C_{j'n'} \tag{5.4}$$

Following this, CRF is used to annualise capital costs by converting its present value into annualised payments over a specified operation lifespan given by t^{max} and its respective discount rate, r. CRF can be determined via Equation 5.5.

$$CRF = \frac{r(1+r)^{t^{max}}}{(1+r)^{t^{max}} - 1} \tag{5.5}$$

In the case where operating lifespans of technologies *j* and *j'* differ from one another, Equations 5.1, 5.4 and 5.5 can be revised to give Equations 5.6 – 5.8. *ACAP* represents the total annualised capital costs.

$$EP = GP - ACAP - MAC \tag{5.6}$$

$$ACAP = \sum_{j=1}^{J}\sum_{n=1}^{N} m_{jn}\mathrm{C}_{jn}\mathrm{CRF}_{jn} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} m_{j'n'}\mathrm{C}_{j'n'}\mathrm{CRF}_{j'n'} \tag{5.7}$$

$$\mathrm{CRF}_l = \frac{\mathrm{r}(1+\mathrm{r})^{\mathrm{t}_l^{\max}}}{(1+\mathrm{r})^{\mathrm{t}_l^{\max}} - 1} \qquad \forall l,\ l \in jn, j'n' \tag{5.8}$$

Aside from this, Equation 5.9 is included in the model to determine *MAC*. As shown, *MAC* is determined based on the design capacities selected for process technologies *j*. $\mathrm{C}_{jn}^{\mathrm{Main}}$ and $\mathrm{C}_{j'n'}^{\mathrm{Main}}$ represent the maintenance cost corresponding to design capacities *n* and *n'* in process technology *j* and *j'* respectively.

$$MAC = \sum_{j=1}^{J}\sum_{n=1}^{N} m_{jn}\mathrm{C}_{jn}^{\mathrm{Main}} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} m_{j'n'}\mathrm{C}_{j'n'}^{\mathrm{Main}} \tag{5.9}$$

Besides installed units, both m_{jn} and $m_{j'n'}$ also represent the level of redundancy of design capacities *n* and *n'* in process technologies *j* and *j'* respectively. As such, the following Section 5.3.3 discusses the approach developed in Chapter 5 to determine the redundancy allocation required to synthesise a reliable BES.

5.3.3 Redundancy Allocation

As mentioned previously, m_{jn} and $m_{j'n'}$ are both determined based on the redundancy allocation required to synthesise a reliable BES. Figure 5.1 shows a generic representation of redundancy allocation addressed in this work. In process technology j, design capacity n in process technology j is selected based on the maximum operating capacity among all s scenarios (as shown in Equation 5.7). As most of the equipment sizes in the market are fixed, Equation 5.7 is included to select from various design capacities available for purchase in process technology j ($\mathrm{F}_{jn}^{\mathrm{Design}}$). In Equation 5.10, $(z_{jn})_s$ is a positive integer which represents the number of operating units with design capacity n selected for process technology j in scenario s.

$$\sum_{n=1}^{N}\left(z_{jn}\right)_s \mathrm{F}_{jn}^{\mathrm{Design}} \geq \left(\sum_{p=1}^{P} F_{jp}^{\mathrm{I}}\right)_s \qquad \forall j \forall s \qquad (5.10)$$

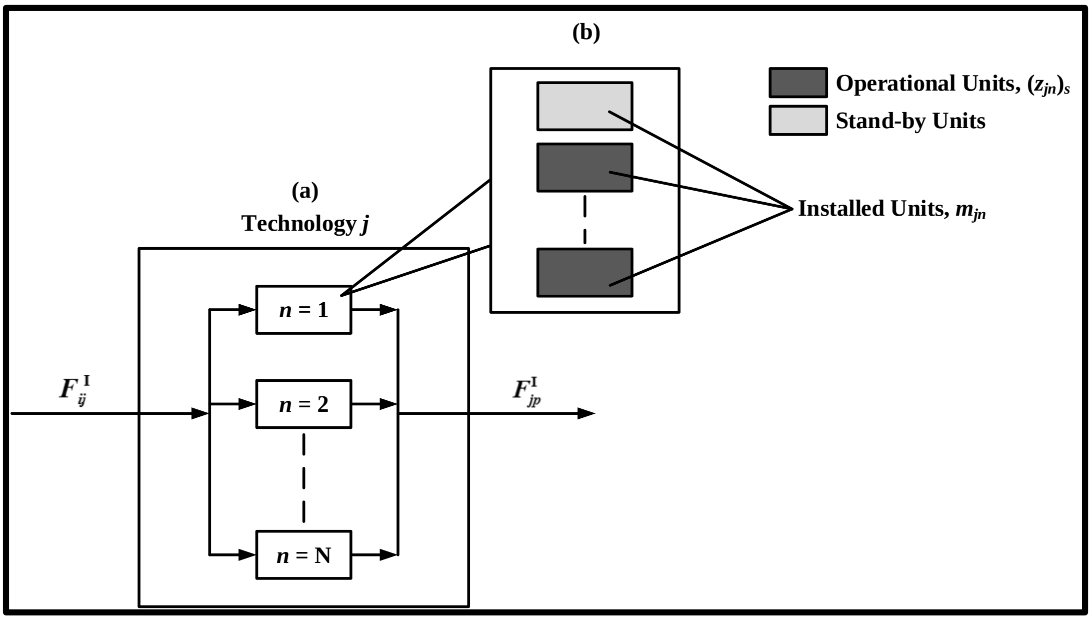

Figure 5.1: Generic Superstructure of (a) Technology *j* with Design Capacities *n*, (b) Redundancy Allocation of Design Capacities *n* in Technology *j*

The number of operating process units with design capacity n (from Equation 5.10) will then activate I_{jn} in Equation 5.11. I_{jn} is a binary integer variable which denotes the presence of a selected process technology j with design capacity n for each scenario s, while M is a large arbitrary value. Furthermore, I_{jn} is constrained in Equation 5.12 to select one type of design capacity n out of N design capacity options considered in Equation 5.10. With Equation 5.12, only one design capacity is chosen instead of a mixture of capacities.

$$\left(z_{jn}\right)_s \leq \left(\mathrm{M} \times I_{jn}\right)_s \qquad \forall j \forall n \forall s \quad (5.11)$$

$$\left(\sum_{n=1}^{N} I_{jn}\right)_s \leq 1 \qquad \forall j \forall s \quad (5.12)$$

The activation of I_{jn} will then trigger a minimum acceptable reliability level for design capacity n in process technology j, denoted by $\mathrm{R}_{jn}^{\mathrm{Min}}$ in Equation 5.13. The minimum reliability level is specified by adapting the principles behind chance-constrained programming (CCP) (Charnes and Cooper, 1959) shown in Equation 2.9. In Equation 2.9, p provides the confidence level of complying with constraints, while $P(Ax \geq b)$ is the actual probability of meeting constraints. Using this principle, the minimum acceptable reliability level in Equation 5.13 functions as the acceptable user-defined confidence level in which j operates for a given period. In other words, it is interpreted as the minimum expected probability of which a configuration in j will operate in a given period.

$$\left(\sum_{n=1}^{N} R_{jn} I_{jn}\right)_s \geq \left(\sum_{n=1}^{N} \mathrm{R}_{jn}^{\mathrm{Min}} I_{jn}\right)_s \qquad \forall j \forall s \qquad (5.13)$$

Based on the minimum acceptable reliability level specified in Equation 5.13, the actual reliability of a given configuration in j with design capacity n, (R_{jn}) is determined. R_{jn} is determined via the k-out-of-m system modelling approach (Coit and Liu, 2000) shown in Equation 5.14. In Equation 5.14, R_{jn} ($m_{jn} \geq k$) represents the probability that k or more (out of m_{jn}) process units are operational in each scenario s. To compute the reliability R_{jn} ($m_{jn} \geq k$), it is assumed that all process units with a design capacity n have the same reliability, P_{jn}. P_{jn} is the probability that an individual process unit with design capacity n performs its function in j. Because of the assumption in P_{jn}, Equation 5.14 uses binomial distribution C to determine the number of installed units, m_{jn} with respect to the minimum acceptable reliability level specified in Equation 5.13. As a result, the required redundancy allocation for design capacities n is determined in j.

$$\left(R_{jn}\left(m_{jn} \geq k\right)\right)_s = \sum_{k=(z_{jn})_s}^{m_{jn}} {}^{m_{jn}}C_k \left(\mathrm{P}_{jn}\right)^k \left(1-\mathrm{P}_{jn}\right)^{m_{jn}-k} \qquad \forall j \forall n \forall s \qquad (5.14)$$

where k = {$(z_{jn})_s$ to m_{jn}} while

$$\left(z_{jn}\right)_s \leq m_{jn} \qquad \forall j \forall n \forall s \qquad (5.15)$$

As with Equations 5.10 – 5.15, Equations 5.16 – 5.21 are included in the model to determine the required redundancy allocation for selected design capacities n' in process technology j';

$$\sum_{n'=1}^{N'} \left(z_{j'n'}\right)_s \mathrm{F}_{j'n'}^{\mathrm{Design}} \geq \left(\sum_{p'=1}^{P'} F_{j'p'}^{\mathrm{II}} \right)_s \qquad \forall j' \forall s \qquad (5.16)$$

$$\left(z_{j'n'}\right)_s \leq \left(\mathrm{M} \times I_{j'n'}\right)_s \qquad \forall j' \forall n' \forall s \qquad (5.17)$$

$$\left(\sum_{n'=1}^{N'} I_{j'n'} \right)_s \leq 1 \qquad \forall j' \forall s \qquad (5.18)$$

$$\left(\sum_{n'=1}^{N'} R_{j'n'} I_{j'n'} \right)_s \geq \left(\sum_{n'=1}^{N'} \mathrm{R}_{j'n'}^{\mathrm{Min}} I_{j'n'} \right)_s \qquad \forall j' \forall s \qquad (5.19)$$

$$\left(R_{j'n'}\left(m_{j'n'} \geq k'\right)\right)_s = \sum_{k'=(z_{j'n'})_s}^{m_{j'n'}} {}^{m_{j'n'}}C_{k'} \left(\mathrm{P}_{j'n'}\right)^{k'} \left(1 - \mathrm{P}_{j'n'}\right)^{m_{j'n'} - k'} \qquad \forall j' \forall n' \forall s \qquad (5.20)$$

where $k' = \{(z_{j'n'})_s$ to $m_{j'n'}\}$ while

$$\left(z_{j'n'}\right)_s \leq m_{j'n'} \qquad \forall j' \forall n' \forall s \qquad (5.21)$$

Note that by including Equations 5.7 and 5.13 in the optimisation model, the chances of an under designed BES will be eliminated. Note also that design capacities $\mathrm{F}_{jn}^{\mathrm{Design}}$ and $\mathrm{F}_{j'n'}^{\mathrm{Design}}$ can be revised according to current market availability in order to produce an up-to-date economic analysis.

To illustrate the proposed approach, two case studies are presented in the next section. In the first case study, a simple steam turbine configuration synthesis case study is solved based on the reliability of each design capacity. In the second case study, the proposed approach is demonstrated with a palm BES case study. Note that for each case study, a mixed integer non-linear programming (MINLP) model is formulated based on mass and energy balances, economic analysis and redundancy allocation equations shown in Equations 4.1 – 4.14, 5.1 – 5.5 and 5.9 – 5.21 respectively. The case studies are then solved via LINGO v14 Global Solver (Gau and Schrage, 2004) in Dell Vostro 3400 with Intel Core i5 (2.40GHz) and 4GB DDR3 RAM. Details of the presented case studies are discussed in Section 5.4.

5.4 Case Studies

5.4.1 Case Study 1

In Case Study 1, it is assumed that the owner of a BES is interested in synthesising a reliable steam turbine configuration with maximum economic performance. The steam turbine configuration is required to deliver output power based on the seasonal requirements shown in Table 5.1 (assuming the boiler is able to supply steam at fixed rate). In addition, Table 5.1 also shows the fraction of occurrence for each respective season. Furthermore, Table 5.2 shows the design capacity options of steam turbines available for purchase and their respective reliabilities. Table 5.3 summarises other economic parameters used for this case study. Following this, the steam turbine configuration is expected to operate on a minimum reliability level of 95%.

Table 5.1: Power Demand and Fraction of Occurrence for Case Study 1

Season	Power Demand (kW)	Fraction of Occurrence
1	489.0	$\alpha_1 = 0.417$
2	225.0	$\alpha_2 = 0.333$
3	289.0	$\alpha_3 = 0.250$

Table 5.2: Available Design Capacity Options for Case Study 1

Design Capacity Options	Capital Costs (US$)	Maintenance Costs (US$/yr)	Reliability
250 kW	90,549	5,000	0.900
500 kW	122,380	10,000	0.910
1 MW	165,395	20,000	0.920

Table 5.3: Economic Parameters for Case Study 1

Operational Hours, AOT	5,000/yr
*Operation Lifespan, t^{max}	15 yr
CRF	0.13/yr
*Discount Rate, r	10%
Price of Power Sold, C_e^{Exp}	0.0900 US$/kWh

*t^{max} and r are assumed to be the same for all technologies considered

Subsequently, a simple superstructure is developed to include all considered turbine options (as shown in Figure 5.2). Each option represents a certain design capacity. Once the design capacity is selected from the superstructure, it is possible to determine the number of equipment units required (as described in Section 5.3.3). These options are then mathematically modelled (according to Equations 4.1 – 4.16, 5.1 – 5.5 and 5.9 – 5.21), allowing quantitative analysis and optimisation. Following this, the developed MINLP model for this case study is solved by maximising Equation 5.1 (as shown in Equation 5.22) to determine the steam turbine configuration with maximum *EP*. Details of the model (e.g., codes, result scripts, CPU time, variables, integers, etc.) for Case Study 1 are included in Section A.2 of the Appendices.

Maximise *EP* (5.22)

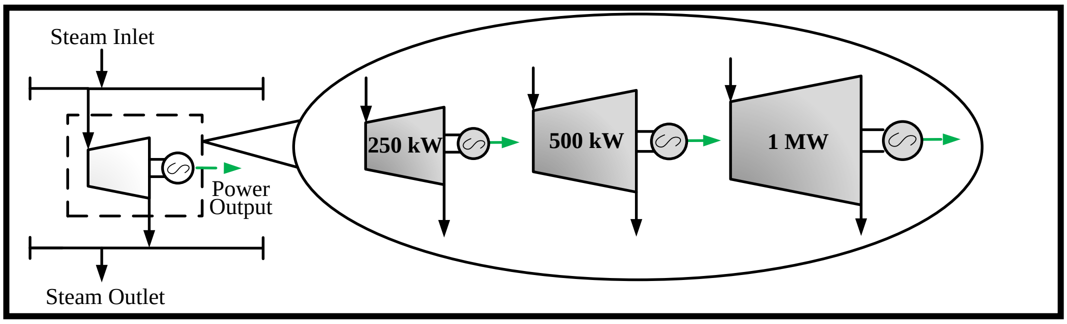

Figure 5.2: Superstructure of Steam Turbine Options for Case Study 1

The resulting steam turbine configuration is shown in Figure 5.3. As shown, the configuration consists of three 250 kW steam turbine units. Besides, Table 5.4 summarises the model output for the synthesised configuration. As shown in Table 4, the *GP*, *CAP* and *MAC* obtained are US$ 162,541/yr, US$ 279,646 and US$ 15,000/yr, respectively. Besides, Table 5.5 shows that the reliability level achieved with this configuration are 0.972, 0.999 and 0.972 for Seasons 1 – 3 respectively. Meanwhile, Figure 5.4 illustrates the state (e.g., operational or standby) of the steam turbines in each season. As shown in Figure 5.4, Season 1 will have two operating turbines while the remaining one will be placed on standby. Since one turbine is available on standby in Season 1, the synthesised configuration would still be able to meet demands if one of the operational turbines fails. In Season 2, only one turbine would be operational while the remaining two would be on standby mode. If the turbine in operation experiences failure, two standby turbines are available to meet power requirements. Therefore, a higher reliability value of 0.999 is obtained in Season 2 compared to 0.972 in Season 1. As in the case of Season 1, two out of the three turbines would be operating in Season 3. If one of the turbines in operation fails, the remaining turbine on standby is still available and capable to resume operations.

Table 5.4: Model Output for Case Study 1

Model Output	
GP (US$/yr)	162,541
CAP (US$)	279,646
MAC (US$/yr)	15,000

Table 5.5: Equipment Status for each Season in Case Study 1

Design Capacity	**Season**	**Status**		**Configuration Reliability**
		Operational, $(z_{jn})_s$	**Standby**	
250 kW	1	2	1	0.972
	2	1	2	0.999
	3	2	1	0.972

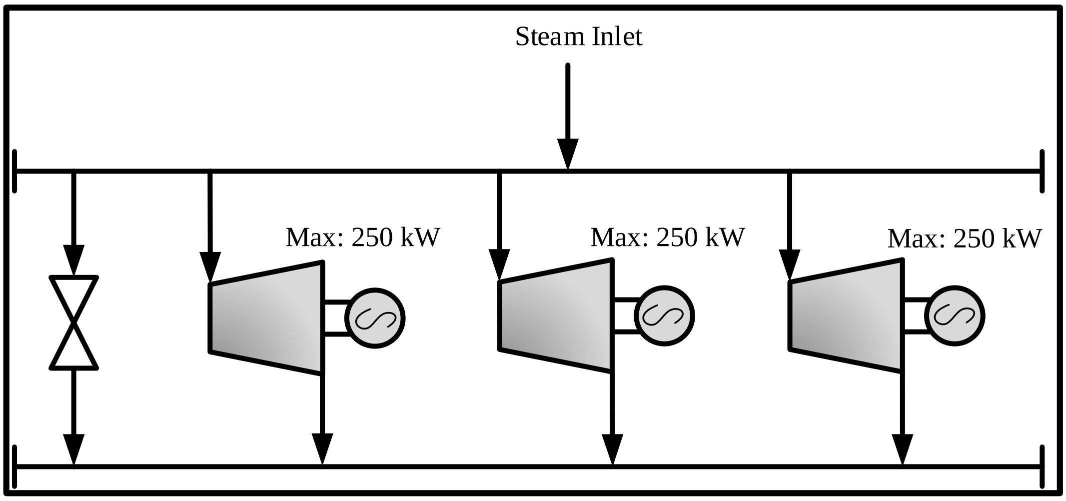

Figure 5.3: Synthesised Steam Turbine Configuration for Case Study 1

Based on the results obtained, a reliable grassroots steam turbine configuration is synthesised to cope with failure and to meet power demands across three considered seasons. To further illustrate the application of the proposed systematic approach, the grassroots design of an entire palm-based BES is discussed in Case Study 2.

5.4.2 Case Study 2

In this example, the case study presented in Chapter 4 is revisited. As shown, Case 1 synthesised a palm BES without taking into account the equipment redundancy allocation. As such, Case Study 2 presents the grassroots design of a reliable palm BES under seasonal variations in biomass supply and energy demand, considering equipment redundancy allocation.

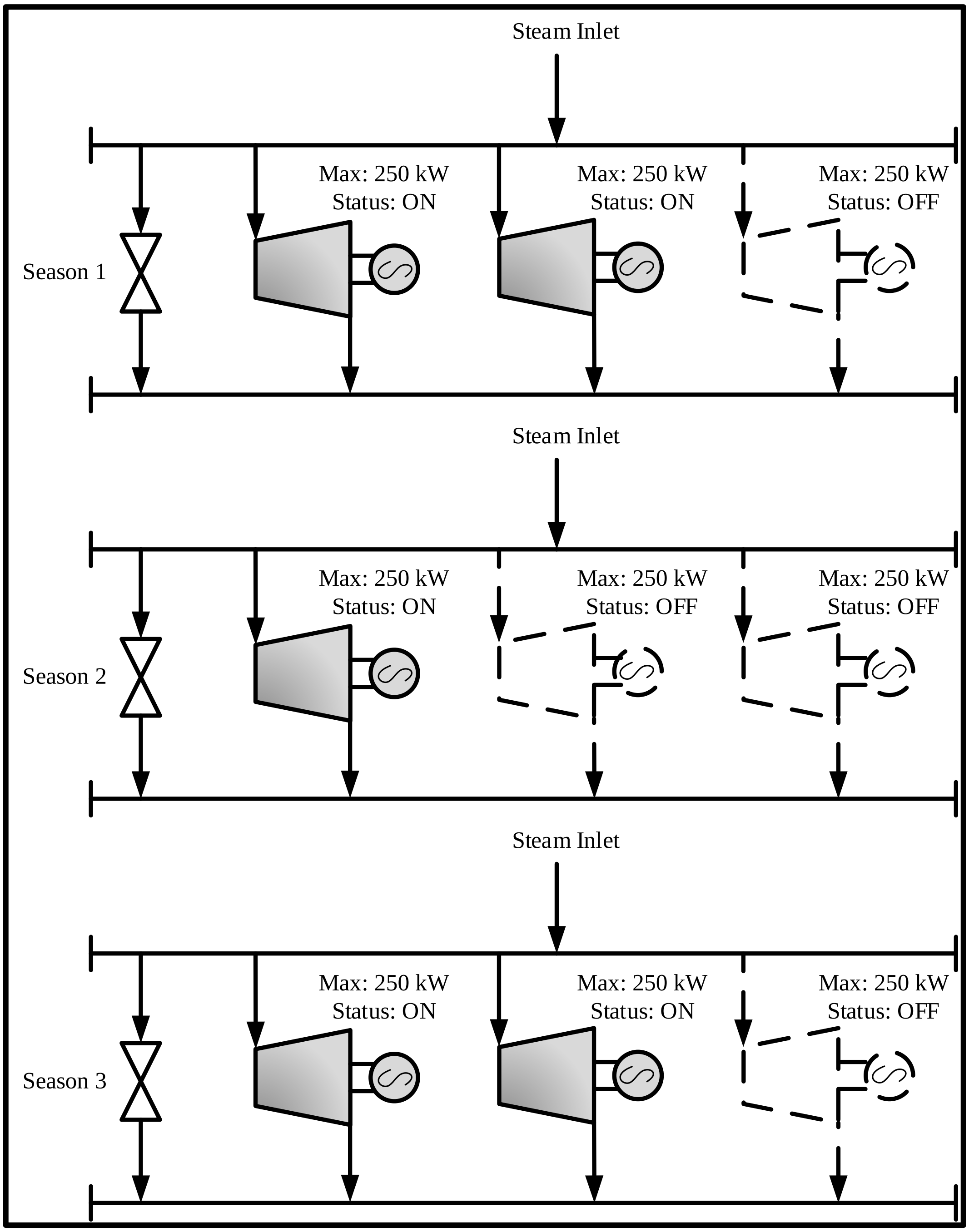

Figure 5.4: Operational and Stand-by Units in Season 1 – 3 for Case Study 1 (Note that units on standby are represented by dotted unit operation symbols)

It is assumed that an investor is interested in implementing a new palm BES which would supply utilities such as power, low pressure steam (LPS), cooling water and chilled water to an existing palm oil mill (POM) (as shown in Figure 4.3). The raw material (palm-based biomass) for the BES is purchased from the POM at the costs shown in Table 4.1. Meanwhile, the utilities produced by the BES would be supplied to POM at the costs given in Table 4.2. The seasonal utility demand and palm-based biomass generated from the POM are summarised in Tables 4.4 – 4.5 respectively. As shown, Case Study 2 considers three seasons with respect to crude palm oil productions which are low, mid and high seasons. Each season is given a fraction of occurrence as shown in Table 4.3. These fractions are assigned based on dividing the duration of a particular season with the total duration in one year.

A superstructure is developed to include all possible process technologies and configurations (as shown in Figure 4.6). Similar to Case Study 1, although only one unit is shown in the superstructure, it is possible to have several units in cases when smaller design capacities are selected (as described in Section 5.3.3). All these alternatives are then mathematically modelled (according to Equations 4.1 – 4.14, 5.1 – 5.5 and 5.9 – 5.21), allowing quantitative analysis and optimisation. A list of available design capacities considered in this case study is provided in Table 4.6. In addition, capital costs for each respective design capacity are summarised in Table 4.6. Table 5.6 shows the maintenance costs and reliability data of the considered design capacities while Table 5.7 shows other economic parameters considered in Case Study 2. Note that reliability data can be obtained from historical equipment databases such as the Offshore Reliability Data (OREDA) Handbook (SINTEF Industrial Management, 2002). In addition, detailed conversion data for this case study are provided in Table 4.7 (from Chapter 4). Note that other operation costs such as labour, administration and plant overhead costs are not considered in this case study.

The developed MINLP model for this case study is solved by maximising Equation 5.1 (as shown in Equation 5.22). Details of the model (e.g., codes, result scripts, CPU time, variables, integers, etc.) for Case Study 2 are presented in Section A.2 of the Appendices. The results obtained upon optimisation are shown in Table 5.8. As shown, *GP* of this case study is found as US$ 2,772,959/yr over its operational lifespan of 15 years. In addition, the total *CAP* and *MAC* of the system are found as US$ 6,770,352 and US$ 112,407/yr respectively. Note that the simple payback period of the synthesised BES (without considering labour, administration and plant overhead costs) is determined as 2.44 years. Note also that the synthesised BES configuration is shown in Figure 5.5. As shown, the synthesised BES include unit operations such as water tube boilers (2 × 12 kg/s), high pressure steam (HPS) turbines (4 × 500 kW), medium pressure steam (MPS) turbines (3 × 250 kW), membrane separation units (3 × 180 kg/h), gas turbines (4 × 500 kW), a heat recovery steam generator (1 × 12 kg/s), an anaerobic digester, a cooling tower, mechanical chiller and a biomass dryer. Meanwhile, Figures 5.6 – 5.8 illustrate the state (e.g., operational or standby) of chosen technologies in the synthesised BES configuration for each season considered. In Figures 5.6 – 5.8, units on standby are represented by dotted unit operation symbols. For instance, in Figure 5.6, 1 of 2 water tube boilers installed would be placed on standby during the lean season. Other units on standby in this season include 2 HPS turbines, 1 MPS turbine, 1 gas turbine and 1 membrane separation unit. As for mid and high seasons (Figures 5.7 – 5.8), the units on standby include 1 water tube boiler, 1 HPS turbine, 1 MPS turbine, 1 gas turbine and 1 membrane separation unit. This is summarised in Table 5.9. Furthermore, Table 5.9 shows the reliability level achieved by the aforementioned technologies in each season. Based on these results, the synthesised BES possesses the required redundancy allocation of unit operations in order to continue operating should there be an event of failure. Aside from this, it is noted that there is a change in the number of operational units for HPS turbines between low to mid and high seasons. This is due to the increase in energy demand during mid and high seasons. The number of units in operation and on standby between seasons are summarised in Table 5.9.

On the other hand, Table 5.10 shows the amount of palm-based biomass utilised by the BES throughout the three considered seasons. It is noted that the consumed palm-based biomass corresponds to the amount utilised to produce energy for the POM, internal BES consumption and the grid. The energy produced is then distributed to meet energy demands of the POM and internal BES consumption. Excess energy, for instance power (if any) is exported to the grid (as shown in Table 5.11).

Table 5.6: Maintenance Costs and Reliability for Considered Technologies in Case Study 2

Technology ***j* and *j'***	**Design Capacity,** F_{jn}^{Design} **and** $F_{j'n'}^{Design}$	**Maintenance Costs,** C_{jn}^{Main} **and** $C_{j'n'}^{Main}$ **(US$/yr)**	**Reliability**	**Minimum Acceptable Reliability for Configuration**
Water Tube Boiler	40 kg/s	40,000	0.920	0.950
	12 kg/s	12,000	0.900	0.950
Fired Tube Boiler	12 kg/s	12,000	0.920	0.950
	10 kg/s	10,000	0.900	0.950
High Pressure	1,000 kW	20,000	0.910	0.950
Steam Turbine	500 kW	10,000	0.900	0.950
Medium Pressure	500 kW	10,000	0.920	0.950
Steam Turbine	250 kW	5,000	0.910	0.950
Gas Turbine	1,000 kW	25,000	0.910	0.950
	500 kW	12,500	0.900	0.950
Internal Combustion Engine	315 kW	27,720	0.920	0.950
	400 kW	35,200	0.900	0.950
Amine Scrubbing	40,000 kg/h	-	0.920	0.950
Pressure Swing Adsorption	25,000 kg/h	-	0.910	0.950
Membrane Separation	10,000 kg/h	-	0.900	0.950

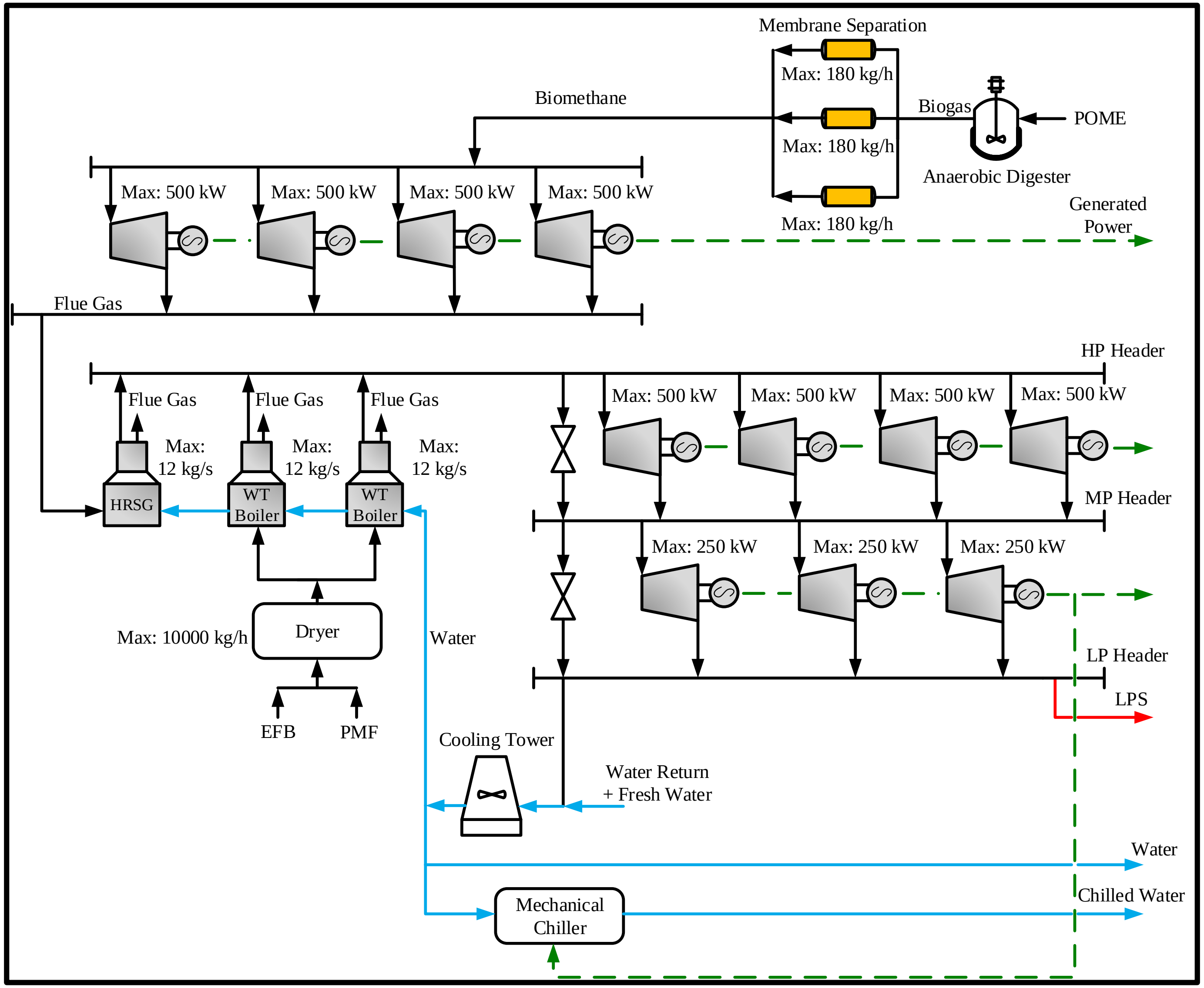

Figure 5.5: Synthesised Palm BES Design for Case Study 2

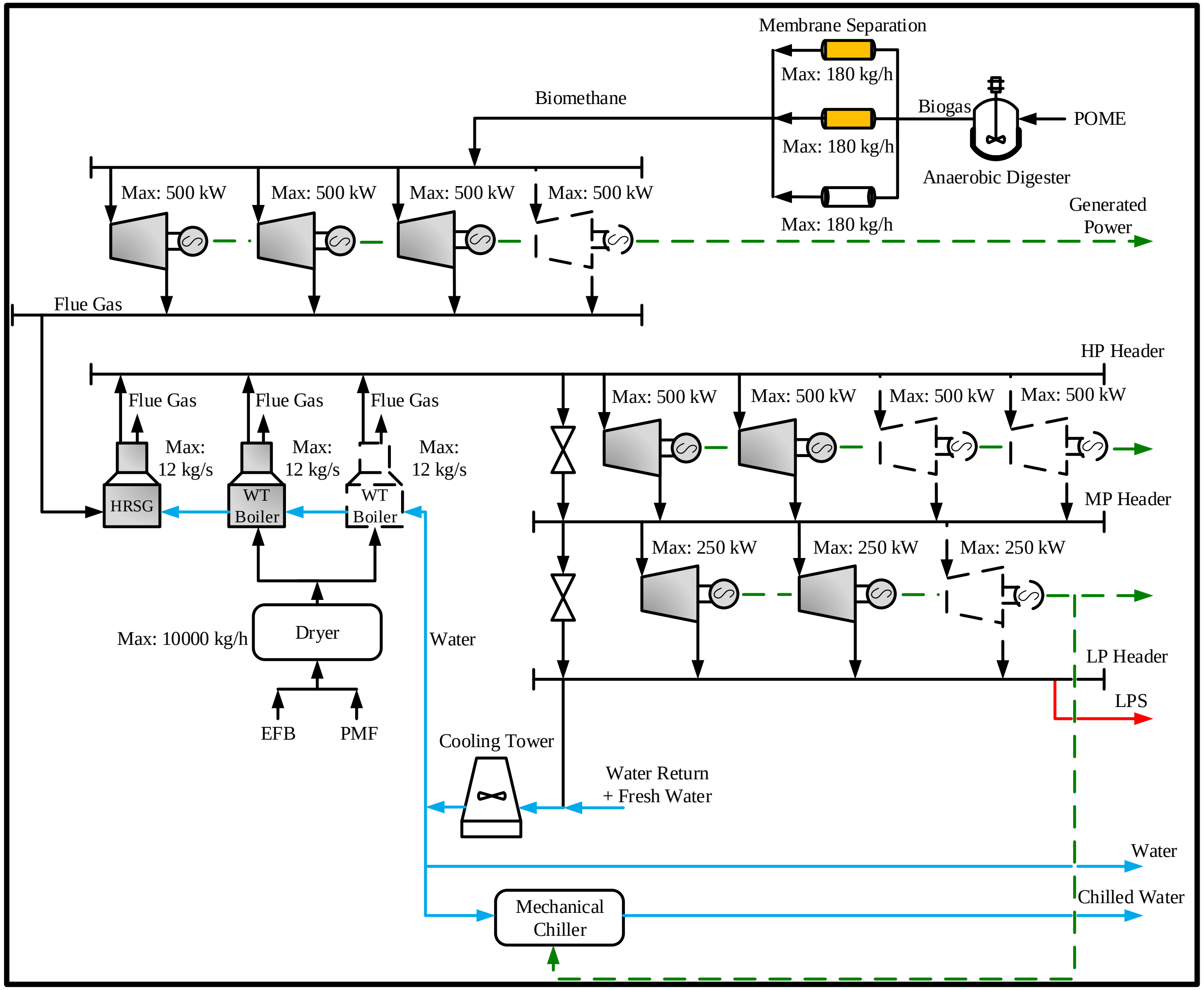

Figure 5.6: Operational and Stand-by Units for Low Season in Case Study 2

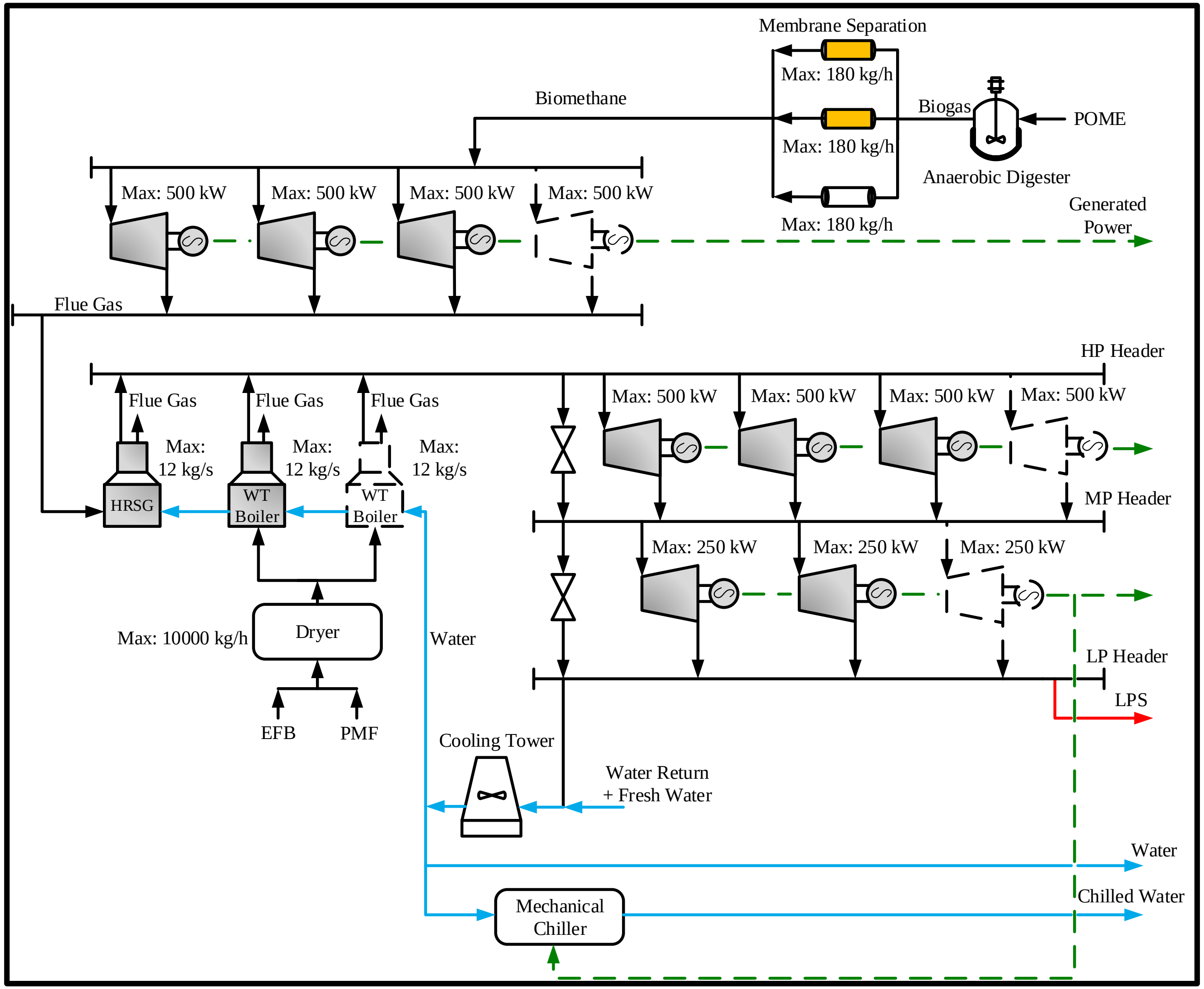

Figure 5.7: Operational and Stand-by Units for Mid Season in Case Study 2

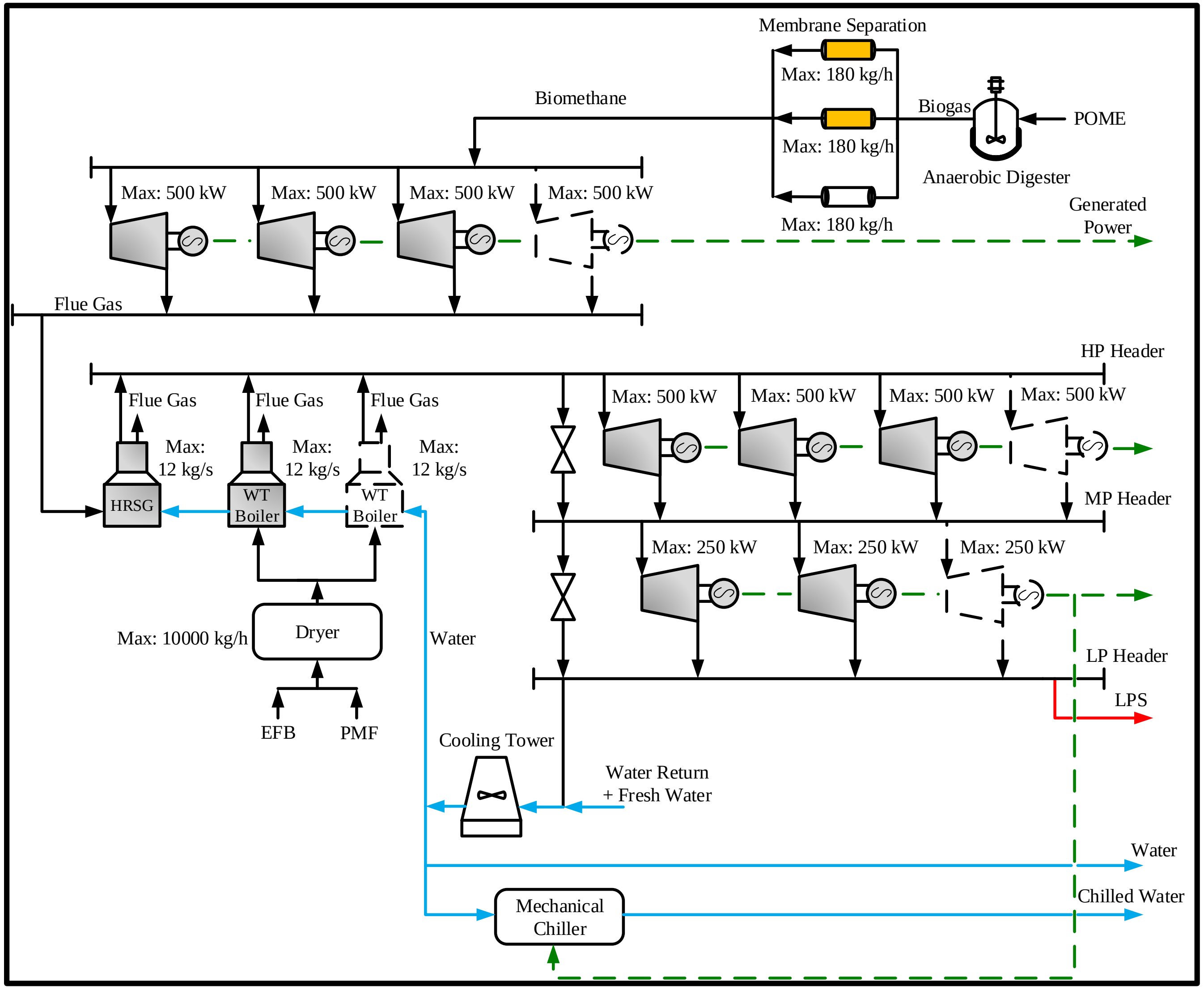

Figure 5.8: Operational and Stand-by Units for High Season in Case Study 2

As compared to results provided in Chapter 4, the BES synthesised in this Case Study 2 utilises PMF, EFB and POME instead of PKS. Meanwhile, results in Chapter 4 (refer to Table 4.12) indicate similar results except that a small fraction of PKS is still utilised for energy production. Since PKS is not utilised in Case Study 2, it has resulted in lesser exportation of power (shown in Table 5.11) compared to results in Chapter 4 (refer to Table 4.13). The difference in results is due to the number of unit operations selected. In this case study, a higher number of units were selected as opposed to the number in Chapter 4. This is because to synthesise a reliable BES, redundant unit operations are purchased. Since more unit operations are purchased, the economic performance is maximised by not purchasing PKS for the BES due to its high purchase price.

Table 5.7: Economic Parameters for Case Study 2

Operational Hours, AOT	5,000/yr
*Operation Lifespan, t^{max}	15 yr
CRF	0.13/yr
*Discount Rate, r	10%

*t^{max} and r are assumed to be the same for all technologies considered

Table 5.8: Model Output for Case Study 2

Model Output	
Average Power Generated (kW)	2,475.6
Average Power to Grid (kW)	1,666.4
Average Power to Palm Oil Mill (kW)	728.3
Average Power from Grid (kW)	0.0
GP (US$/yr)	2,772,959
CAP (US$)	6,770,352
MAC (US$)	112,407
Payback Period (yr)	2.44

Table 5.9: Chosen Technologies for Case Study 2

Technology	Design Capacity	No. Installed	Status			Configuration Reliability
			Season	No. Standby	No. Operating	
WT-Boiler	12 kg/s	2	1	1	1	0.990
			2	1	1	0.990
			3	1	1	0.990
HPS Turbine	500 kW	4	1	2	2	0.997
			2	1	3	0.957
			3	1	3	0.957
MPS Turbine	250 kW	3	1	1	2	0.977
			2	1	2	0.977
			3	1	2	0.977
Gas Turbine	500 kW	4	1	1	3	0.957
			2	1	3	0.957
			3	1	3	0.957
Membrane Separation	180 kg/h	3	1	1	2	0.972
			2	1	2	0.972
			3	1	2	0.972
Heat Recovery Steam Generator	12 kg/s	1		0	1	-
Dryer	10,000 kg/h	1		0	1	-
Mechanical Chiller	250 kW	1		0	1	-
Cooling Tower	25 kg/s	1		0	1	-
Anaerobic Digester	Based on Available flow	1		0	1	-
Total Units		**21**				

Table 5.10: Available and Consumed Palm-Based Biomass for Case Study 2

Season	Biomass	Available (kg/h)	Consumed (kg/h)
Low	EFB	12,375.00	12,375.00
	PMF	6,875.00	6,779.90
	PKS	3,437.50	0.00
	POME	40,700.00	40,700.00
Mid	EFB	14,625.00	14,625.00
	PMF	8,125.00	8,012.60
	PKS	4,062.50	0.00
	POME	48,100.00	48,100.00
High	EFB	16,875.00	16,875.00
	PMF	9,375.00	9,245.00
	PKS	4,687.50	0.00
	POME	55,500.00	55,500.00

Table 5.11: Power Distribution for Case Study 2

Season	Power Distribution	Power (kW)
Low	To Mill	632.5
	Internally	70.2
	To Grid	1,447.2
Mid	To Mill	747.5
	Internally	83.0
	To Grid	1,710.4
High	To Mill	862.5
	Internally	95.7
	To Grid	1,973.5

5.5 Summary

A systematic approach has been developed to synthesise a reliable grassroots BES design considering equipment redundancy to handle seasonal variations in supply and demand. In this approach, the *k*-out-of-*m* system modelling is applied with chance-constrained programming to determine the required redundancy allocation for a considered technology in a BES. In addition, the presented approach addresses complex decisions such as whether to install additional large capacity equipment units, or multiple smaller capacity units, based on their unique reliability levels. The proposed approach simultaneously screens technologies from a range of alternatives based on their respective equipment reliability, capital and operating costs. It also determines equipment design capacities along with the total number of operating (and stand-by) equipment based in various operating scenarios. The presented approach has been illustrated using two case studies. The next chapter extends the redundancy allocation approach in Chapter 5 to incorporate the operating strategy of a BES as part of design considerations.

CHAPTER 6

SYNTHESIS OF BIOMASS-BASED ENERGY SYSTEMS: TECHNOLOGY SELECTION, SIZING AND REDUNDANCY ALLOCATION BASED ON OPERATIONAL STRATEGY

6.1 Introduction

In the previous chapter, a systematic approach was developed to consider equipment allocation for grassroots design of a reliable biomass-based energy system (BES). However, selecting, sizing and redundancy allocation cannot be decided without consideration of the BES operating strategy. The operation strategy is the critical factor governing the overall performance of any BES. With a suitable operating strategy, a BES is able to reduce overall fuel consumption and operational costs. As such, Chapter 6 proposes a systematic approach to design a BES that is robust toward its operating strategies. The proposed approach is able to simultaneously determine type, size and required equipment redundancy (e.g., operating and standby units) of technologies while considering operating strategies in a BES. A palm BES case study is solved to illustrate the proposed approach.

6.2 Problem Statement

Previously in Chapters 4 and 5, index *s* is defined to represent the operating scenario for multi-period optimisation. This concept is adapted in Chapter 6, to define *s* as the operating strategy to design a BES. As such, the design problem addressed in Chapter 6 is stated as follows: Given a strategy *s*, a set of biomass *i* with flow rate, F_i^{BIO} and its composition $q \in Q$ can be converted to primary product $p \in P$ through process technologies $j \in J$. Primary product *p* and its composition $q' \in Q'$ can then be further converted to final products $p' \in P'$ via process technologies $j' \in J'$. Besides producing primary and final products *p* and *p'*, process technologies *j* and *j'* can also generate energy $e \in E$ (illustrated in Figure 4.1). Aside from this, design capacities $n \in N$ and $n' \in N'$ are available in the market to be purchased for technology *j* and *j'* respectively (shown in Figure 5.1). The objective of Chapter 6 is to develop a systematic approach to determine the type, size and redundancy allocation of technologies for a BES that is robust towards its operational strategies $s \in S$ (as shown in Figure 6.1). The following section further explains the mathematical optimisation model developed in Chapter 6.

6.3 Mathematical Optimisation Formulation

Sections 6.3.1 – 6.3.2 describe material and energy balance formulations for each operating strategy *s* based on Figure 6.1. The corresponding economic formulations are then described in Section 6.3.3. Lastly, Section 6.3.4 explains the formulation approach to determine the redundancy allocation of a BES.

6.3.1 Material and Energy Balance

As mentioned previously, scenario *s* in Chapters 4 and 5 is used to define the operating strategy for the design of a BES. In this respect, the material and energy balance formulations shown in Chapter 4, i.e., Equations 4.1 – 4.16 respectively, are used in Chapter 6. Note that Equation 4.16 is used as a general representation of the energy balance for a given operating strategy *s* in Chapter 6. Equation 4.16 can be modified based on the considerations in the operating strategy *s* (e.g., FEL, FTL, etc.) as shown; Let *s* = 1 represent the Following Thermal Load (FTL) operating strategy, while *e* = 1 and *e* = 2 denote heating and power respectively. Based on the fundamental concept of FTL, the overall energy balance in Equation 4.14 is modified to give;

$$\left(E_1^{\mathrm{Gen}}\right)_1 = \left(E_1^{\mathrm{Con}} + E_1^{\mathrm{Demand}} + E_1^{\mathrm{Exp}}\right)_1 \tag{6.1}$$

$$\left(E_2^{\mathrm{Gen}} + E_2^{\mathrm{Imp}}\right)_1 = \left(E_2^{\mathrm{Con}} + E_2^{\mathrm{Demand}} + E_2^{\mathrm{Exp}}\right)_1 \tag{6.2}$$

Meanwhile, let *s* = 2 represent the Following Electrical Load (FEL) operating strategy, while *e* = 1 and *e* = 2 denote heating and power respectively. Based on the fundamental concept of FEL, the overall energy balance in Equation 4.16 is modified to give;

$$\left(E_1^{\mathrm{Gen}} + E_1^{\mathrm{Imp}}\right)_2 = \left(E_1^{\mathrm{Con}} + E_1^{\mathrm{Demand}} + E_1^{\mathrm{Exp}}\right)_2 \tag{6.3}$$

$$\left(E_2^{\mathrm{Gen}}\right)_2 = \left(E_2^{\mathrm{Con}} + E_2^{\mathrm{Demand}} + E_2^{\mathrm{Exp}}\right)_2 \tag{6.4}$$

6.3.2 Economic Aspects

The economic feasibility of the BES is evaluated in this section. Typically, gross profit is used in optimisation studies as a measurement of economic feasibility as shown in Chapter 4. However, selling prices for utilities produced from the BES (e.g., *p'* and *e*) would highly depend on terms agreed between the BES and its client. In this respect, it would be more appropriate to modify the general economic assessment in Chapter 4 to evaluate the economic feasibility of a BES based on its total annualised cost (*TAC*). To determine *TAC*, Equation 6.5 is included in the optimisation model, where OP_s, CRF, *CAP* and *MAC* represent the operating costs for each operating strategy *s*, capital recovery factor, total capital costs and total maintenance costs of the BES respectively.

$$TAC = \sum_{s=1}^{S} OP_s + \mathrm{CRF} \times CAP + MAC \tag{6.5}$$

OP_s can be determined using Equation 6.6, where AOT_s is the annual operating time for operating strategy *s*, $\mathrm{C}_e^{\mathrm{Imp}}$ is the cost of importing external energy *e* and $\mathrm{C}_i^{\mathrm{BIO}}$ is the cost of raw material (lignocellulosic biomass *i*) respectively.

$$OP_s = \mathrm{AOT}_s \times \left(\sum_{e=1}^{E} E_e^{\mathrm{Imp}} \mathrm{C}_e^{\mathrm{Imp}} + \sum_{i=1}^{I} F_i^{\mathrm{BIO}} \mathrm{C}_i^{\mathrm{BIO}} \right)_s \quad \forall s \tag{6.6}$$

On the other hand, *CAP* is determined based on the selected design capacities for technologies *j* and *j'* respectively (Equation 6.7). In Equation 6.7, C_{jn} and $\mathrm{C}_{j'n'}$ represent the capital cost for process technology *j* and *j'* with design capacities *n* and *n'* respectively. Meanwhile, m_{jn} and $m_{j'n'}$ are positive integers that represent the total number of installed units of design capacity *n* and *n'* in *j* and *j'* respectively.

$$CAP = \sum_{j=1}^{J}\sum_{n=1}^{N} m_{jn}\mathrm{C}_{jn} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} m_{j'n'}\mathrm{C}_{j'n'} \tag{6.7}$$

Following this, CRF is used to annualise capital costs by converting its present value into annualised payments over a specified operation lifespan given by t^{max} and its respective discount rate, r. CRF can be determined via Equation 6.8.

$$\mathrm{CRF} = \frac{\mathrm{r}(1+\mathrm{r})^{\mathrm{t}^{max}}}{(1+\mathrm{r})^{\mathrm{t}^{max}} - 1} \tag{6.8}$$

However, if operating lifespans of technologies *j* and *j'* differ from each other, Equations 6.5, 6.7 and 6.8 can be revised to give Equations 6.9 – 6.11. *ACAP* represents the total annualised capital costs.

$$TAC = \sum_{s=1}^{S} OP_s + ACAP + MAC \tag{6.9}$$

$$ACAP = \sum_{j=1}^{J}\sum_{n=1}^{N} m_{jn}\mathrm{C}_{jn}\mathrm{CRF}_{jn} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} m_{j'n'}\mathrm{C}_{j'n'}\mathrm{CRF}_{j'n'} \tag{6.10}$$

$$\mathrm{CRF}_l = \frac{\mathrm{r}(1+\mathrm{r})^{\mathrm{t}_l^{max}}}{(1+\mathrm{r})^{\mathrm{t}_l^{max}} - 1} \qquad \forall l,\ l \in j, j' \tag{6.11}$$

Next, Equation 6.12 is included in the model to determine *MAC*. As shown, *MAC* is determined based on the design capacities selected for process technologies

j. $\mathrm{C}_{jn}^{\mathrm{Main}}$ and $\mathrm{C}_{j'n'}^{\mathrm{Main}}$ represent the maintenance cost corresponding to design capacities n and n' in process technology j and j' respectively.

$$MAC = \sum_{j=1}^{J}\sum_{n=1}^{N} m_{jn}\mathrm{C}_{jn}^{\mathrm{Main}} + \sum_{j'=1}^{J'}\sum_{n'=1}^{N'} m_{j'n'}\mathrm{C}_{j'n'}^{\mathrm{Main}} \tag{6.12}$$

Both m_{jn} and $m_{j'n'}$ also represent the level of redundancy of design capacities n and n' in process technologies j and j' respectively. As such, Section 6.3.4 discusses the approach used in this work to determine the redundancy allocation required for a BES design.

Figure 6.1: Generic Representation for Design based on Operation Strategies *s ϵ S*

6.3.3 Redundancy Allocation

As mentioned previously, m_{jn} and $m_{j'n'}$ are both determined based on the redundancy allocation required to synthesise a BES design. The redundancy allocation formulations shown in Chapter 5, i.e., Equations 5.10 – 5.21 respectively, are used in Chapter 6.

The approach presented in this section is generic and can be applied when one, two or more operating strategies are considered. Based on the operating strategies considered, the design of a BES is determined by minimising Equation 6.5 as shown in Figure 6.1. In this study, a BES steam turbine configuration synthesis case study is solved considering three scenarios, all with unique operating strategies. Details of the case study is described in the following section.

6.4 Case Study

In this case study, a potential owner intends to synthesise a biomass-based energy system (BES) that would supply energy to a palm oil mill (POM) requiring 850.0 kW of power and 13631.0 kW of heat at a minimum reliability level of 95% (0.950). As mentioned previously, it is important to screen various alternative configurations and to allocate the required equipment redundancy based on operating strategies considered (e.g., FEL, FTL and etc.). As such, this case study aims to synthesise a steam turbine configuration with acceptable equipment redundancy based on three different scenarios. In the first scenario, the steam turbine configuration is designed based on the FEL operating strategy. For the second scenario, the FTL operating strategy is considered for the design. Meanwhile, the third scenario considers both FEL and FTL strategies simultaneously to design a robust configuration. In all three scenarios, the design capacities available for purchase are 250 kW and 500 kW. Details of their respective capital costs, maintenance costs and reliabilities as shown in Table 6.1. Note that reliability data of the equipment can be obtained from historical equipment databases such as the

Offshore Reliability Data (OREDA) Handbook (SINTEF Industrial Management, 2002). Table 6.2 shows the economic and operational parameters used for this case study. All three scenarios in this case study are solved using LINGO v14 Global Solver (Gau and Schrage, 2004) in Dell Vostro 3400 with Intel Core i5 (2.40GHz) and 4GB DDR3 RAM. Details of the models (e.g., codes, result scripts, CPU time, variables, integers, etc.) for all three scenarios are included in Section A.3 of the Appendices.

Table 6.1: Steam Turbine Options for Case Study

Operating Range	Capacity Options (kW)	Capital Cost (US$)	Maintenance Cost (US$/yr)	Reliability
Mid Pressure	250	100,000	5,000	0.900
	500	130,000	10,000	0.910
High Pressure	250	120,000	5,000	0.900
	500	155,000	10,000	0.910

Table 6.2: Economic and Operational Parameters for Case Study

Parameters	Units	Value
Power from Grid	US$/kWh	0.1200
Water Supply	US$/kg	0.0023
Palm-based Biomass	US$/kg	0.0022
Biomass Boiler Cost	US$	2,000,000
Auxiliary Boiler Cost	US$	1,000,000
*Capital Recovery Factor (CRF)	/yr	0.13
Boiler Efficiency	%	75.0
Palm-based Biomass Calorific Value	kJ/kg	19,000.0
Steam Turbine Efficiency	%	70.0
Steam Enthalpy (at 20 bar)	kJ/kg	3,137.5
Steam Enthalpy (at 10 bar)	kJ/kg	2,901.6
Steam Enthalpy (at 5 bar)	kJ/kg	2,855.8

*CRF is assumed to be the same for all technologies considered

Scenario 1: Design based on Following Electrical Load (FEL) Strategy

As mentioned previously, Scenario 1 considers the design of a steam turbine configuration based on the FEL operation strategy. In this scenario, a superstructure of alternative configurations is first developed and showed in Figure 6.2. As shown, the superstructure consists of a biomass boiler and three possible turbine routes to meet power demands based on the FEL strategy. The biomass boiler utilises palm mesocarp fibre (PMF) as fuel to generate high pressure steam (HPS) from a water supply. Following this, HPS can be sent to T3 to generate power by expanding the HPS from 20 bar to mid pressure steam (MPS) of 10 bar. Alternatively, HPS can be expanded from 20 bar to low pressure steam (LPS) of 5 bar via T2. Besides, another alternative is to divide the load between the levels 20 bar to 10 bar and 10 bar to 5 bar to supply MPS and LPS simultaneously as shown in route T1a/T1b. As mentioned earlier, this operating strategy is totally independent of the power utility grid. However, if the heat demand of the POM is higher than the generated amount, an auxiliary boiler (AB) with additional capital cost of US$ 1,000,000 may be selected as shown in Table 6.2. Note that the superstructure in Figure 6.2 only indicates information on technological routes available for selection.

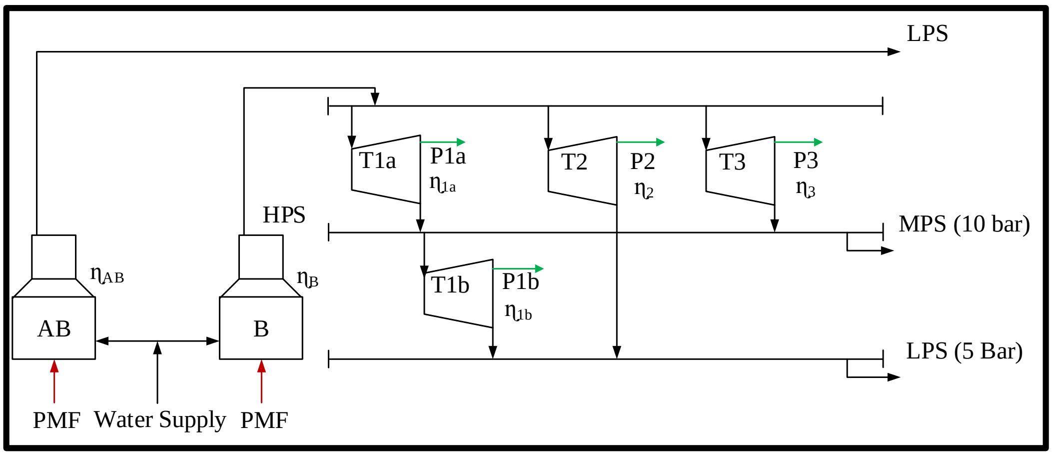

Figure 6.2: FEL Superstructure for Case Study – Scenario 1

Based on Figure 6.2, a mathematical model is formulated according to Equations 4.1 – 4.16, 5.10 – 5.21 and solved by minimising *TAC* as shown in Equation 6.13. The resultant configuration is shown in Figure 6.3 while its respective *TAC*, *MAC*, *OP* and *CAP* outputs are summarised in Table 6.3. Moreover, route chosen for operation in this scenario is T3, which meets power load and produces an excess heat of 1304.5 kW. The total amount of water supply and biomass consumed are 5.15 kg/s and 1.31 kg/s respectively. The *TAC*, *OP*, *MAC* and *CAP* outputs of the synthesised configuration are summarised in Table 6.3 respectively. Upon selecting route T3, the model determines the sizing and redundancy allocation of the equipment. Model performs sizing by screening design capacities based on cost, and the number of operating units required. With the number of operating units, the number of redundant equipment is determined. Figure 6.3 shows the resultant configuration after technology selection, sizing and redundancy allocation. As shown in Figure 6.3, three steam turbines with design capacities of 500 kW were chosen for purchase. Among these three turbines, two are expected two operate while the remaining one turbine would be kept on stand-by, resulting in an overall reliability of 0.977. If one of the operational turbines fails, the turbine on standby can still be operated to meet energy demands.

$$\text{Minimise } TAC \tag{6.13}$$

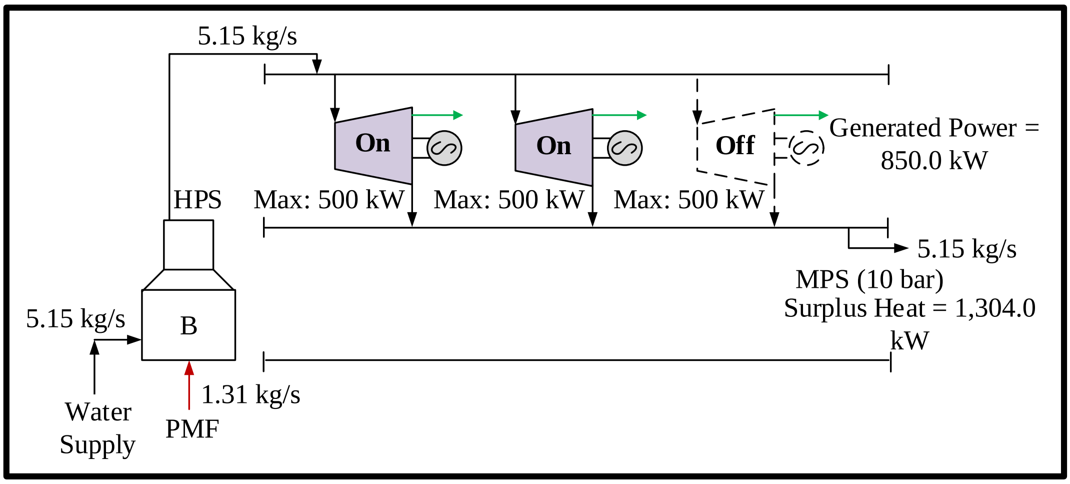

Figure 6.3: Synthesised Configuration based on FEL Strategy (Scenario 1)

Scenario 2: Design based on Following Thermal Load (FTL) Strategy

In Scenario 2, the steam turbine configuration is designed according to thermal energy requirements of the POM. The superstructure developed for Scenario 2 is shown in Figure 6.4. In the case where the electricity demand exceeds the generation capacity, the deficit can be compensated by purchasing additional power from the grid at a rate shown in Table 6.2. Similar to Scenario 1, a mathematical model is formulated based on Figure 6.4. The model is then solved (via Equation 6.13) to yield *TAC*, *MAC*, *OP* and *CAP* outputs shown in Table 6.3. The route selected in scenario is T2, whereby HPS is expanded to the LPS in order to meet the thermal load while generating surplus power of 91.2 kW. The total amount of water supply and biomass consumed are 4.77 kg/s and 1.22 kg/s respectively. Based on the chosen route, Figure 6.5 shows that three steam turbines with design capacities of 500 kW were chosen for purchase. Among these three turbines, two are expected two operate while the remaining one turbine would be kept on stand-by, resulting in an overall reliability of 0.977. In the case where one operational turbines fails, the turbine on standby can be operated to meet energy demands.

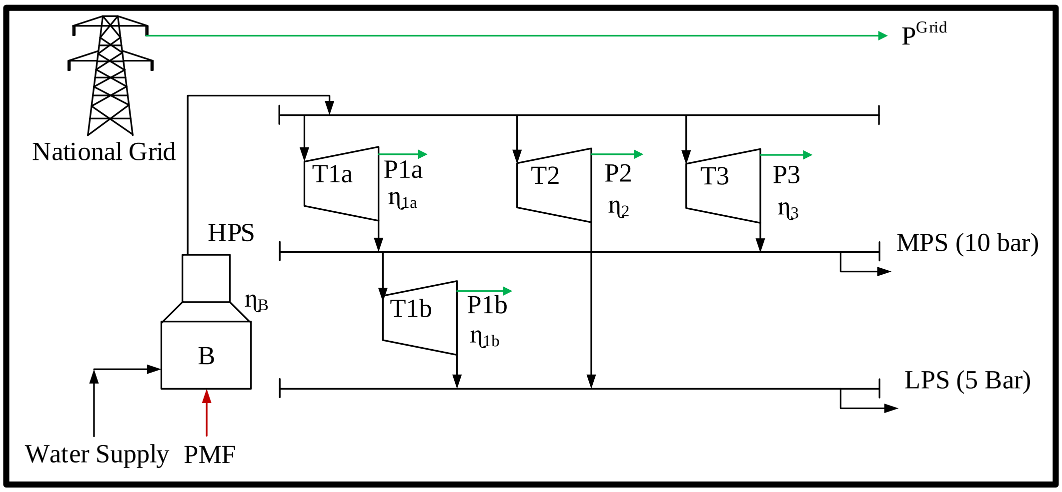

Figure 6.4: FTL Superstructure for Case Study – Scenario 2

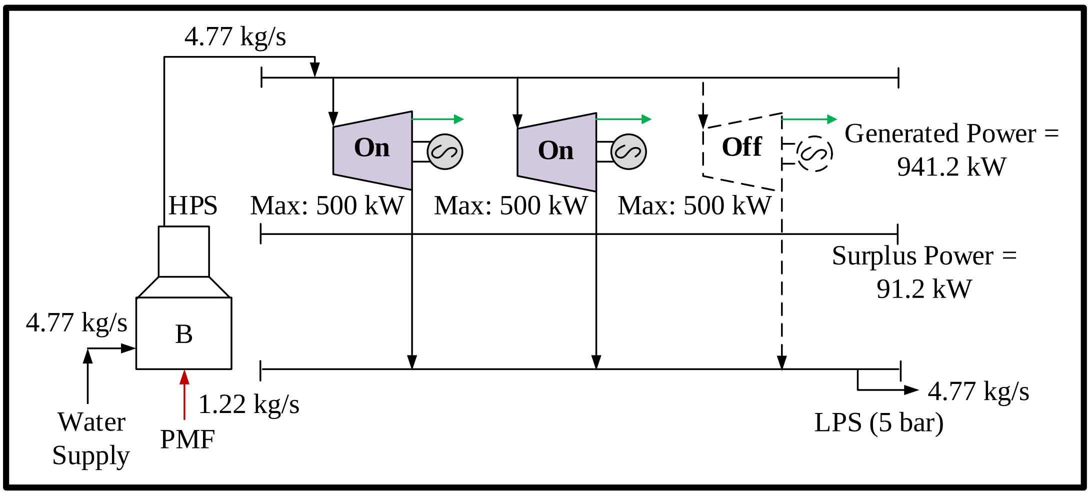

Figure 6.5: Synthesised Configuration based on FTL Strategy (Scenario 2)

<u>Scenario 3: Robust Design for FEL and FTL Operating Strategies</u>

As shown in Figure 6.6, this scenario considers both FEL and FTL operating strategies simultaneously to design a robust steam turbine configuration using the proposed approach in Section 6.3. The result of this scenario is a design that is able to operate on a robust strategy without any wastage of energy. Based on Figure 6.6, the mathematical model is formulated and solved (via Equation 6.13). The model output is summarised in Table 6.3. The multi-stage route (T1a/T1b) is chosen for this scenario. In the multi-stage route, Figure 6.7 shows that three steam turbines with design capacities of 500 kW were allocated for the HPS to MPS level while two steam turbines with design capacities of 250 kW were allocated for the MPS to LPS level. Among the three turbines at the HPS to MPS level, two are expected to operate while the remaining one turbine would be kept on stand-by, resulting in a configuration reliability of 0.977. Meanwhile, one out of the two turbines at the MPS to LPS is required to operate, resulting in a configuration reliability of 0.990. Since both levels are in series and interdependent, the overall reliability for the multi-stage configuration is taken as the product of the two respective reliabilities (0.977 × 0.990) according to reliability theory. As such, the overall reliability is determined as 0.967. The operating steam turbines do not generate surplus power while the total amount of water supply and biomass consumed are 4.73 kg/s and 1.21 kg/s respectively. Meanwhile, *TAC*, *CAP*, *OP* and *MAC* outputs of the synthesised configuration in Scenario 3 are shown in Table 6.3.

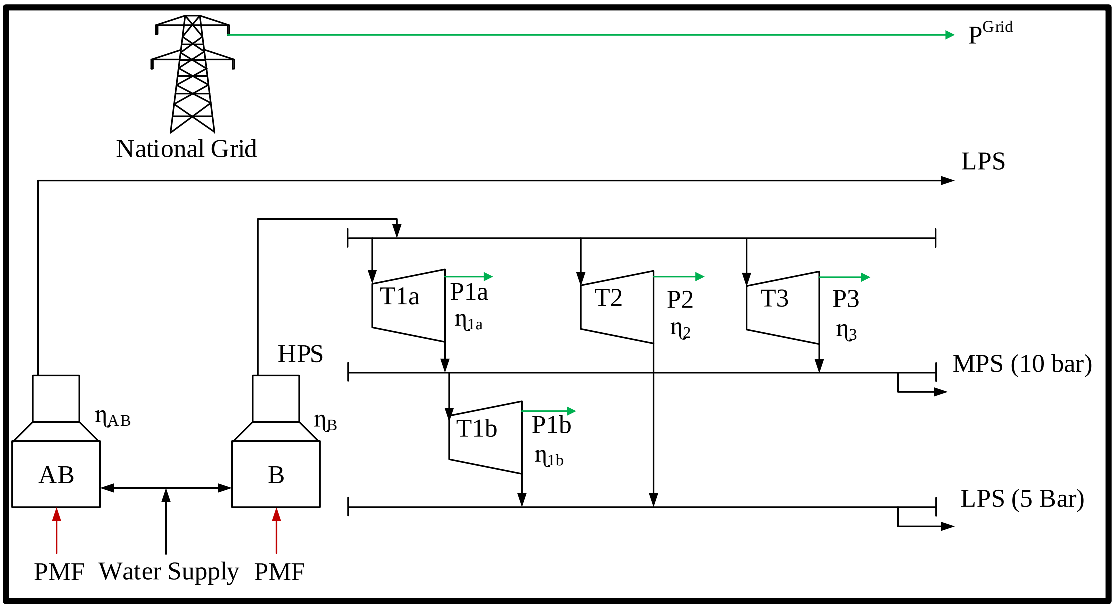

Figure 6.6: Superstructure for Case Study – Scenario 3

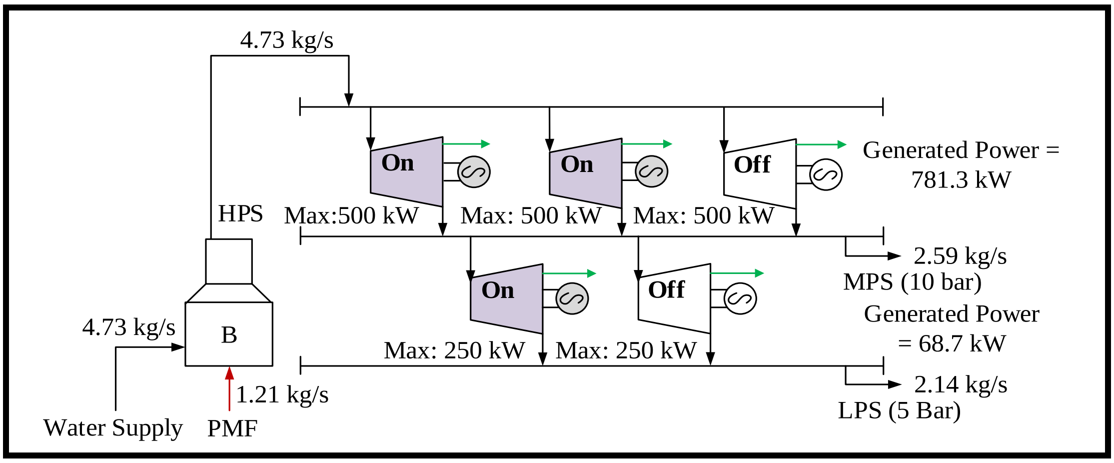

Figure 6.7: Flowrates Allocation for Robust Design (Scenario 3)

6.5 Results Analysis

Table 6.3 summarises the results obtained for Scenarios 1 – 3. As shown in Table 6.3, the *TAC* in Scenario 2 is lower than in Scenario 1 despite having the same *CAP* and *MAC*. This is because the configuration chosen in Scenario 2 expands produced HPS at a much higher pressure gradient (HPS to LPS expansion) as compared to Scenario 1 (HPS to MPS expansion). As such, the configuration in Scenario 2 utilises lesser water supply and biomass while generating more power than in Scenario 1, resulting in lower operating costs and consequently lower *TAC*. In addition, Scenario 2 generates surplus power of 91.2 kW which can be utilised for internal purposes. In the case where internal usage is minimal, the excess power can be supplied to the national grid. Meanwhile, it is found that Scenario 1 emits excess steam of 1,304.0 kW. In practice, this excess heat is released to the atmosphere as it is rare for neighbouring facilities to consume such incremental amount of waste heat.

It is worth noting that both FEL and FTL strategies generate excess energy (thermal or electrical). In order to eliminate or minimise excess energy, a BES would require an optimised strategy. An optimised strategy in this sense, is one that is able to switch between FEL and FTL strategies depending on the energy demand. To achieve this, the conventional approach is to overlap and combine components from Scenario 1 and 2 into a unified flowsheet as shown in Figure 6.8. However, such approach would yield configurations with very high *CAP* and *TAC*. Alternatively, changes or modifications can be made to each design from Scenarios 1 – 2 in order to provide switching capabilities. If the FEL design from Scenario 1 is expected to switch to FTL at some point of its operation, Figure 6.9 suggests the FEL design would require additional power from the grid. This because the FEL design generates insufficient amount of power when switched to the FTL mode. Since power is imported from the grid, it would result in a much higher *OP* and *TAC*. Meanwhile, if the FTL design in Scenario 2 is switched to FEL mode, an auxiliary boiler would be required to meet heat load (as shown in Figure 6.10). This is because insufficient heat is generated when the FTL design is switched to FEL. As a result, the addition of an auxiliary boiler would increase *CAP* and *TAC*.

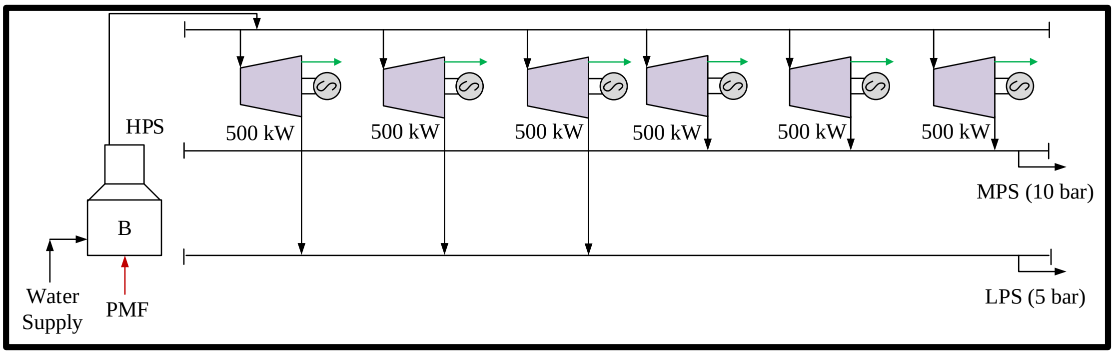

Figure 6.8: Combination of Designs from Scenarios 1 – 2

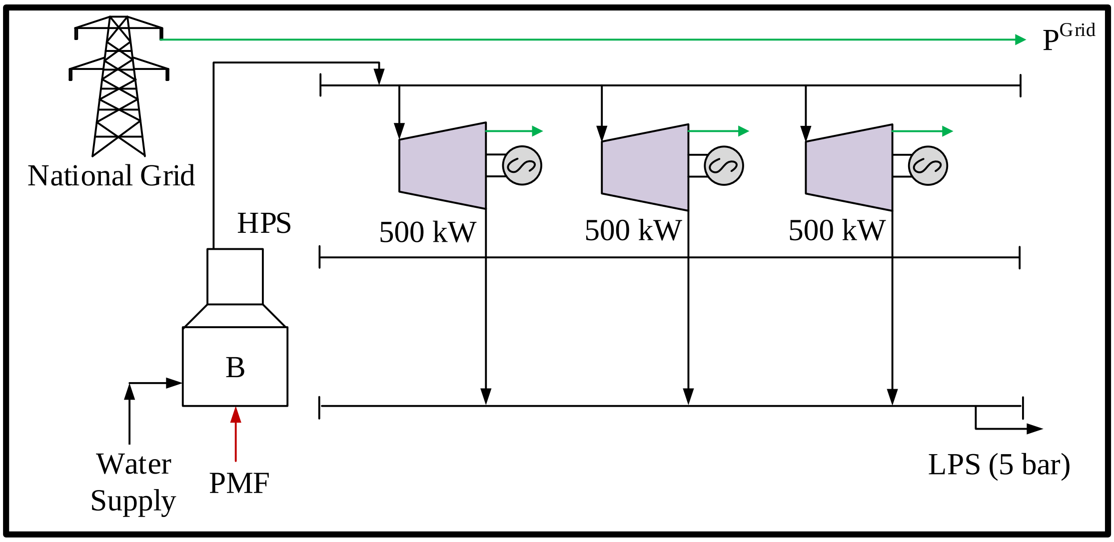

Figure 6.9: Design when FEL in Scenario 1 switches to FTL

On the other hand, Scenario 3 considered both FEL and FTL strategies simultaneously and produced a robust BES configuration. According to Table 6.3, the configuration in Scenario 3 has the lowest operating costs as compared to Scenarios 1 – 2 because it utilises the lowest amount of water and biomass. Despite the low operating costs, Scenario 3 yields the highest *CAP* and *MAC* due to the high number of turbines installed. It is also important to note that the Scenario 3 does not generate surplus power or heat during operations. This is a desired characteristic especially if the BES is required to operate on strict environmental regulations where wastage of energy is not tolerated.

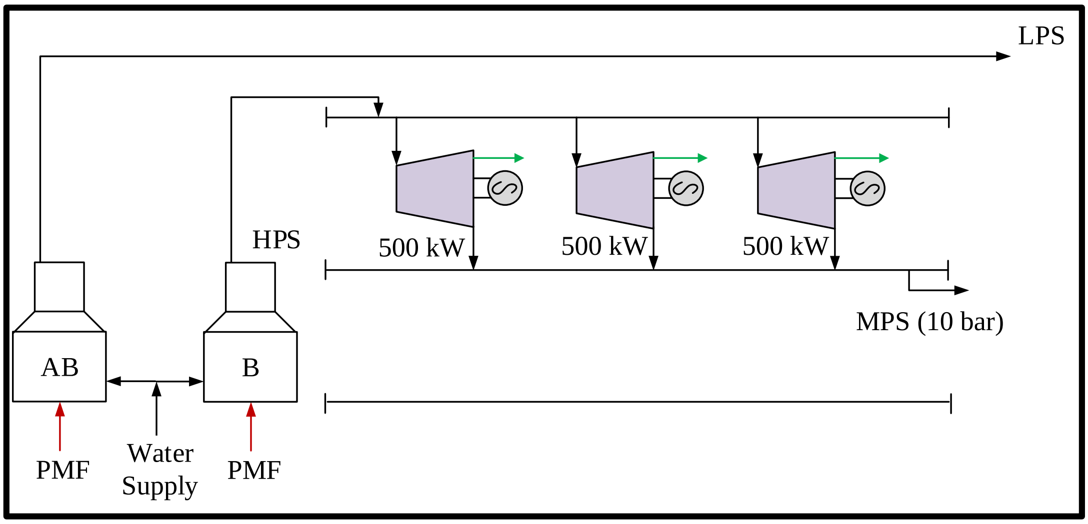

Figure 6.10: Design when FTL in Scenario 2 switches to FEL

On a different note, the configuration in Scenario 3 is able to cope with various occurrences of failure (Figures 6.11 – 6.12). As shown in Figure 6.11, when one turbine on each steam level fails (due to breakdown or maintenance), there is sufficient back-up turbines allocated for response. In the unfortunate case where both MPS turbines fail (Figure 6.12), the configuration in Scenario 3 is able to adopt the same operation in Scenario 1, at the expense of higher operating costs. Nevertheless, the design is still able to cope with the aforementioned equipment failures.

Table 6.3: Model Output for Scenarios 1 – 3

Costs	Scenario 1	Scenario 2	Scenario 3
TAC (US$/yr)	1,084,088	1,030,749	1,060,829
CAP (US$)	2,465,000	2,465,000	2,665,000
OP (US$/yr)	733,638	680,299	674,379
MAC (US$/yr)	30,000	30,000	40,000

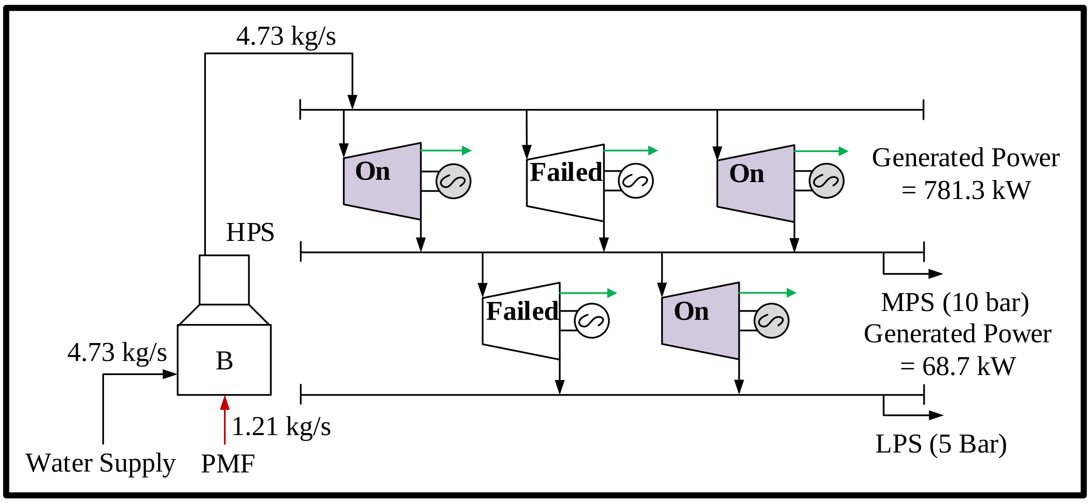

Figure 6.11: Response of Robust Design during Failure in each Level

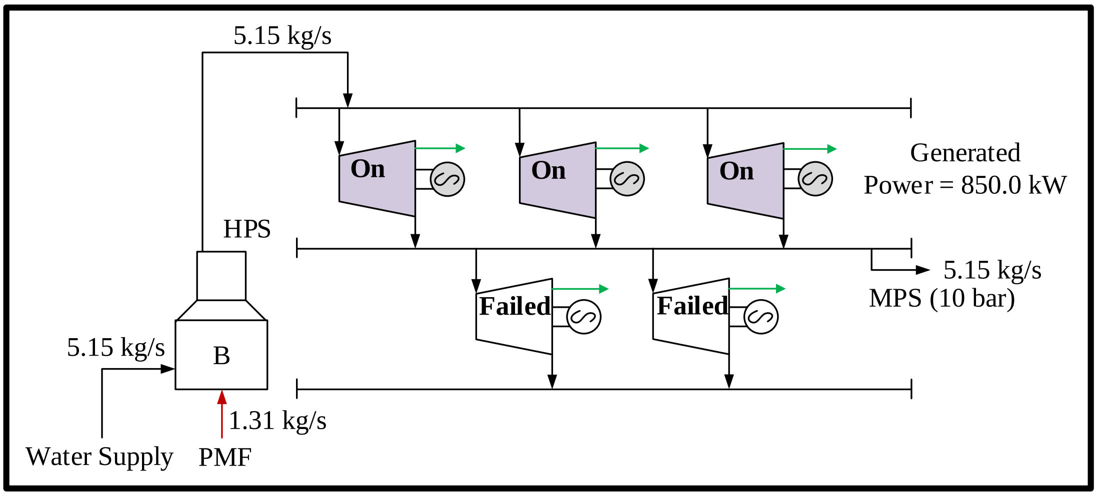

Figure 6.12: Response of Robust Design when Unfortunate Failure in MPS Turbines

6.6 Summary

A systematic approach has been developed in Chapter 6 to synthesise a BES robust towards its operating strategy. The developed approach performs technology selection, sizing and redundancy allocation based on operation strategies. The developed approach was illustrated using a palm-BES case study. As Chapters 4 – 6 provided several approaches to synthesise a BES, the next chapter provides a systematic framework on Design Operability Analysis (DOA) for BES designs synthesised.

CHAPTER 7

SYSTEMATIC FRAMEWORK FOR DESIGN OPERABILITY ANALYSIS (DOA) OF BIOMASS-BASED ENERGY SYSTEMS

7.1 Introduction

In Chapters 5 and 6, biomass-based energy system (BES) is designed based on minimum reliability levels. Below this specified minimum level would mean failure. However, the presented approaches does not consider what would happen to the system when failure occurs. Chapter 7 presents a systematic framework on Design Operability Analysis (DOA). DOA looks at analysing the maximum possible level of operability for the BES and also determines when a BES fails. The presented framework consists of two important steps; the disruption scenario analysis (DSA) and the feasible operating range analysis (FORA). In DSA, equipment failure scenarios are studied to determine if a synthesised BES design configuration is able to remain operable, despite facing disruptions. Meanwhile, the FORA studies the inherent feasible operating range of the synthesised BES. The feasible operating range accounts for the interdependency between utilities produced and represents a range of net utility output a BES can deliver within its design and performance limitations. This range allows designers to recognise the true operating potential of the system and use it to validate its performance for intended seasonal energy demands. To illustrate the proposed framework, a palm BES design from Chapter 5 is used as a case study.

7.2 Systematic Framework for Design Operability Analysis (DOA)

As shown in Figure 7.1, the DOA framework consists of two important steps. The first being the DSA, while the second being the FORA. The Sections 7.2.1 – 7.2.2 further elaborate these steps.

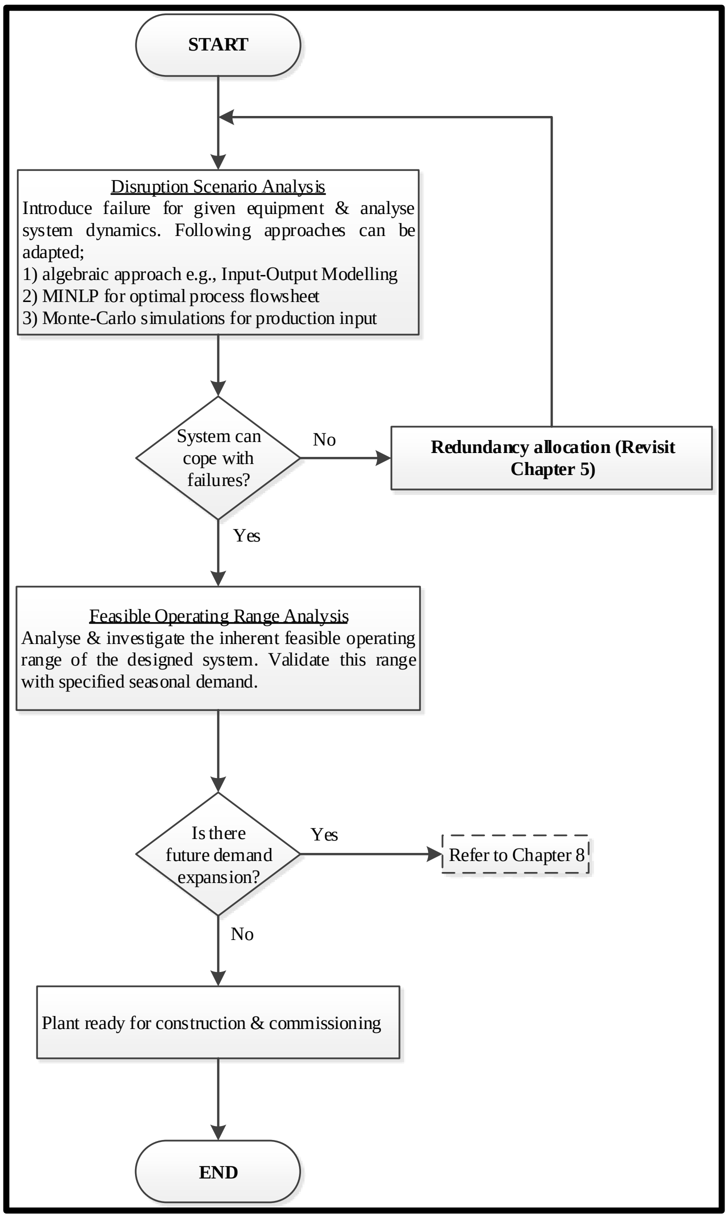

Figure 7.1: Framework for Design Operability Analysis (DOA)

7.2.1 Disruption Scenario Analysis (DSA)

As shown in Figure 7.1, the framework starts with a DSA. This is to study the range of equipment failure scenarios to determine if the synthesised configuration is able to remain operable. To conduct DSA, various approaches can be adapted to represent the analysed system. These approaches may include (but not limited to) algebraic approaches such as input-output modelling, mathematical programming (e.g., mixed integer nonlinear programming) for optimal flowsheeting, Monte-Carlo simulations, etc. In the case where the synthesised configuration is unable to cope with the failure scenarios introduced during the analysis, process designers are required to revert back to the previous design approaches in Chapters 4 – 5. In this step, optimisation parameters considered (e.g., minimum reliability level) can be revised to design an improved BES. If the system is able to cope with the failures introduced, it can then proceed to the next step. In the next step, a FORA is performed on the analysed system. The details of the FOR A is discussed in Section 7.2.2.

7.2.2 Feasible Operating Range Analysis (FORA)

In Chapter 4, a BES is synthesised to deliver a given seasonal energy demand. During the synthesis stage, several alternative technologies are evaluated, screened and chosen based on their respective discrete design capacities available in the market. However, each chosen technology may possess unique minimum and maximum feasible capacities in which they can operate at. This in turn may influence the overall system operating range. In this respect, it is important to analyse the feasible operating range of the system as it highly depends on the equipment constraints or bottlenecks of its highly integrated system.

The feasible operating range can be determined via FORA. In FORA, the inherent feasible operating range of the designed system is determined. The feasible operating range is a function of the process network topology as well as the stable operating range of individual process units themselves. The feasible operating range is a range of net utility output a BES can deliver without experiencing infeasibility due to design and performance limitations. It accounts for the interdependency between utilities produced by a BES. This range allows designers to recognise the true operating potential of the system and use it to validate its performance for an intended seasonal energy demand. The FORA is performed by determining minimum and maximum net output flowrates for each utility supplied. The general procedure for the FOR A are as follows;

1. Let A, B, C be the net output flowrates of utilities supplied by a designed BES.

2. Flowrate of output A is varied while keeping the B and C constant to determine its minimum and maximum flowrates. The minimum value for A is the lowest value of A before the system reaches an infeasible operation. Meanwhile, maximum value for A is the highest value of A before the system reaches an infeasible operation. This is represented in Figure 7.2(a).

3. Step 2 is then repeated for a different output values of B (shown in subsequent data points in Figure 7.2(a)). The corresponding minimum and maximum flowrates for A are noted respectively. Based on the values plotted in Figures 7.2(a), the common region for the values of A is then identified as shown by the blue shaded region.

4. Steps 2 and 3 are then repeated for several output values of C as shown in Figures 7.2(b) – 7.2(c).

5. The common regions of A obtained from in Figures 7.2(a) – 7.2(c) are then plotted on a separate Figure 7.3. By plotting the common blue regions of A on Figure 7.3, the feasible operating region of the BES is then identified. The feasible operating region is represented by the overlapping region of A values (shown in red on Figure 7.3). This overlapping region is considered the region of outputs in which a BES can operate at without experiencing system capacity limitations.

It is important to note that if the utilities considered for analysis exceed 3, it may not be possible to express in the form of a (4 or 5 dimensional) diagram. However, the feasible operating range can be still determined by the overlapping regions of each point. This is done by taking the highest common value of the minimum points and the lowest common value of maximum points without the aid of a diagram.

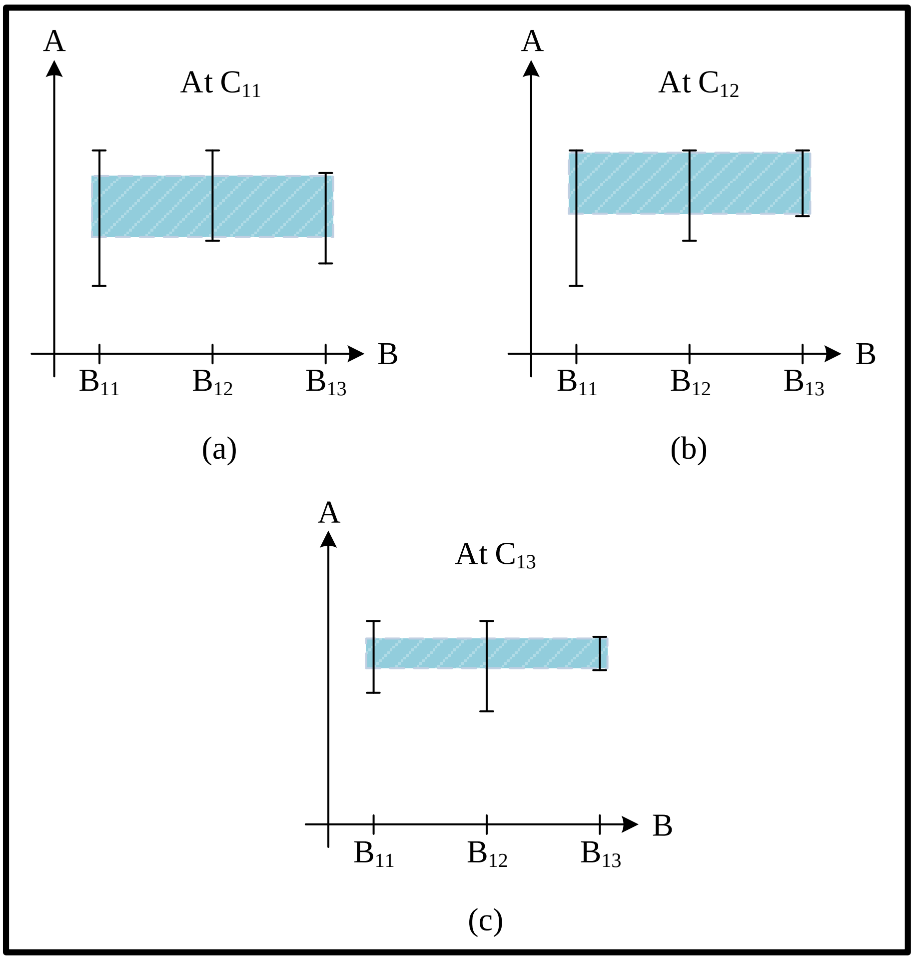

Figure 7.2: Feasible Operating Range Analysis (FORA)

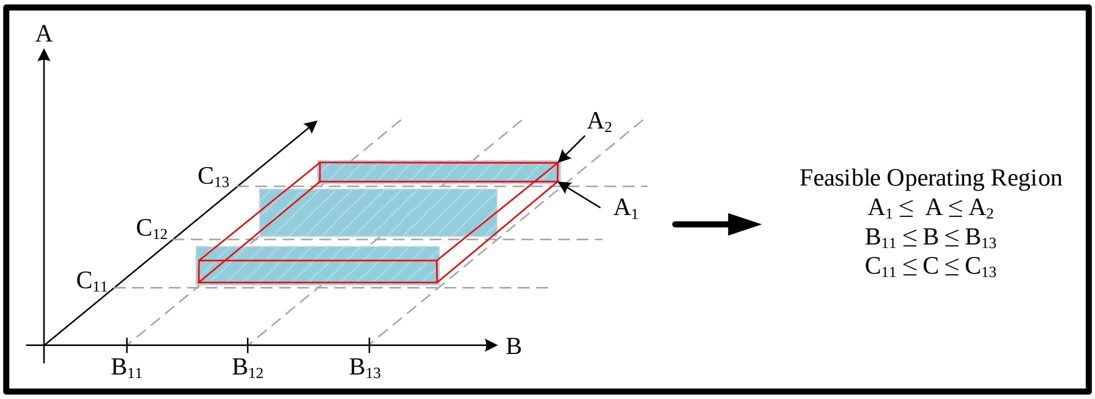

Figure 7.3: Identification of Feasible Operating Range

As mentioned previously, the FOR allows process designers to understand the range of net output (i.e., maximum and minimum of each output) in which the synthesised system can deliver without succumbing to system infeasibility and capacity constraints. Such information not only enables designers to analyse the BES performance with the intended seasonal demand requirements, but also provide an idea of the potential changes that can be made in production throughput if demand variations are considered future. In the case of future variation, the presented framework is extended. Details of this extension are discussed in Chapter 8. Even when no provisions can be made to accommodate for future changes, designers are at least forced to document these considerations. This information can be very useful in the future during operation. Finally, the design configuration can be recommended for construction and commissioning.

The subsequent section of this paper presents a case study to illustrate the proposed framework in Figures 7.1 – 7.3 in a more detailed manner. The model adapted in the case study is also provided to better appreciate the validation process. The case study gives a stepwise procedure in validating BES design from Chapter 5.

7.3 Case Study

In this case study, the framework presented in Figure 7.1 is used to analyse a palm BES synthesised in the design phase. To initiate this framework, an appropriate approach needs to be selected to model the designed state of the plant. This selection procedure is important as it helps to recognise the complexity involved in the process modelling and hence determines the most suitable approach. The analysis process for in this case study adapts the inoperability input-output model (IIM) used in Kasivisvanathan et al. (2013) to determine the optimal operational adjustments when disruptions occur in multi-functional energy systems. IIM is an approach proposed by Haimes and Jiang (2001) to analyse the failure of interdependent infrastructure systems (described by a system of linear equations) suffering from disruption events. Since this approach entails linear correlations, the material and energy balances of the entire system can be expressed as shown by the following equation:

$$\Sigma\, a_{wj}\, x_j = \Sigma\, y_w \tag{7.1}$$

where a_{wj} represents the matrix of input and output fractions to and from a certain unit operation, x_j represents the operating fraction of a unit operation (0 is to denote unit is shut down and 1 is to denote unit is at 100% operation, i.e., baseline capacity), and y_w represents the net flowrate of a given component, which can be a product or feedstock. Note that y_w assumes positve values for streams that are purely products, negative values for streams that are purely input, or zero for streams that are purely intermediates. During operation of the BES, x_j may be adjusted within limits:

$$x_j^{\mathrm{L}}\, b_j \;\leq\; x_j \;\leq\; x_j^{\mathrm{U}}\, b_j \qquad \forall j \tag{7.2}$$

where x_j^{L} and x_j^{U} are the lower and upper limits of operating capacity of process unit j, respectively. The upper limit represents the true maximum capacity of process unit j including safety factors.

Table 7.1: Seasonal Utility Demand for BES

Utility	Unit	Low Season	Mid Season	High Season
Power	kW	2,177.1	2,497.7	2,796.0
Low Pressure Steam (LPS)	kg/h	20,625.00	24,375.00	2,8125.00
Cooling Water	kg/h	11,000.00	13,000.00	15,000.00
Chilled Water*	kg/h	1,000.00	1,000.00	1,000.00

In order to demonstrate the analysis process presented, the design synthesised in Chapter 5 is modelled based on Equations 7.1 – 7.2 and analysed. Figure 7.4 shows the process flow diagram of the BES. Table 7.1 summarises the seasonal energy demand in which the BES is required to meet. Meanwhile, Table 7.2 shows the type of equipment in the BES as well as their respective minimum and maximum feasible capacities. Table 7.3 summarises the overall material and energy balances for the process which also includes the internal production and consumption of intermediates (i.e., with a net output of zero). Note that the positive and negative values in the table represent the outputs and inputs to the process, respectively. The information in Tables 7.2 – 7.3 is then used to formulate the IIM for the BES. In the input-output model, each unit operation in the BES is treated as a "black box" whereby the entire system can be adequately described by a system of linear equations to correlate one process unit to another. The IIM model for this case study is MILP in nature and is solved via LINGO v14 (Branch and Bound Solver) (LINDO Systems Inc., 2011) with Dell Vostro 3400 with Intel Core i5 (2.40GHz) and 4GB DDR3 RAM. Details of this model (e.g., codes, result scripts, CPU time, variables, integers, etc.) can be found in Section A.4 of the Appendices. The IIM developed is then used to perform DSA and the FOR analysis.

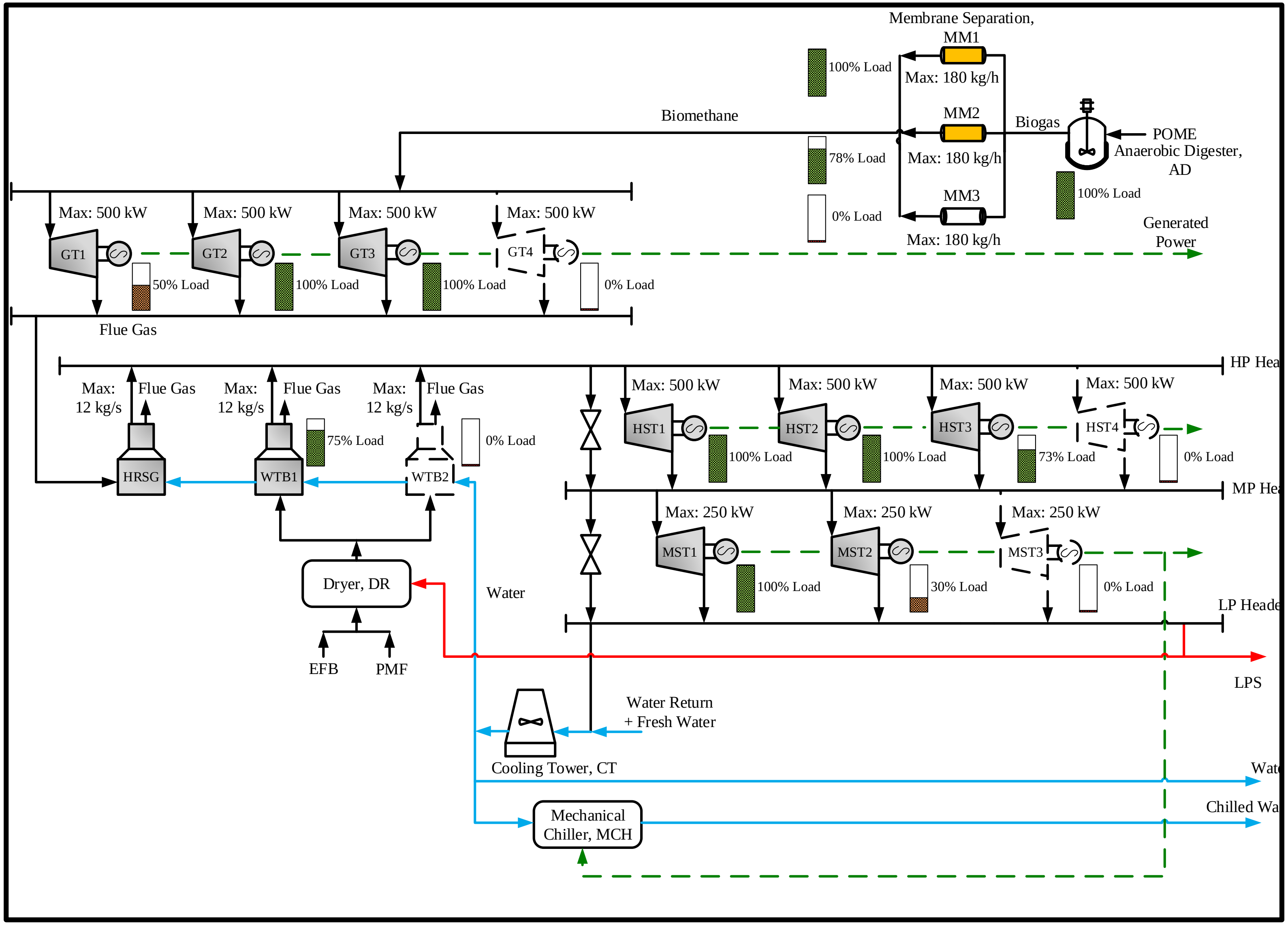

Figure 7.4: System Configuration of Palm BES

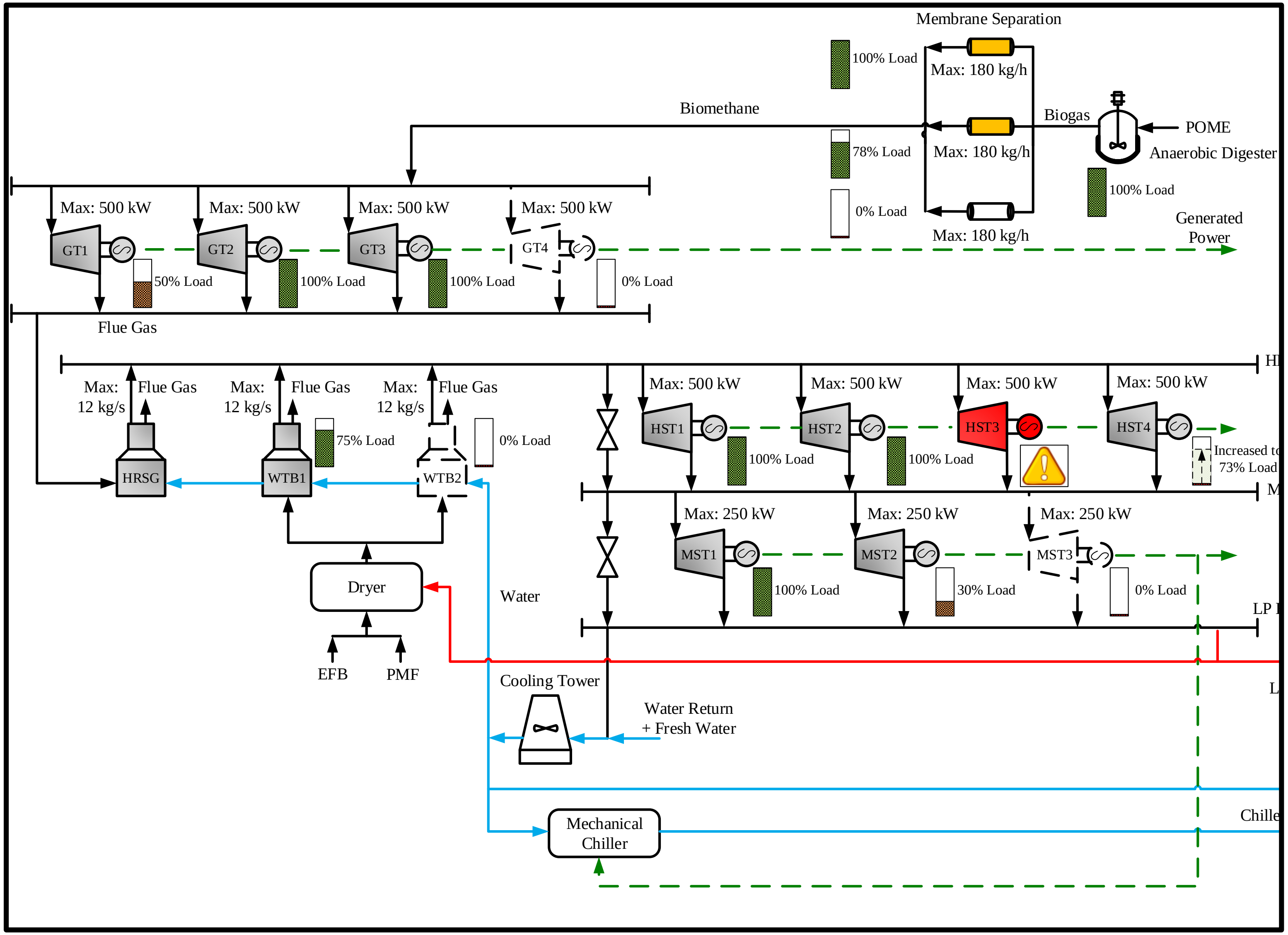

Figure 7.5: DSA for Case Study - Turbine Failure Response

Table 7.2: Minimum and Maximum Feasible Capacities for Equipment in BES

Equipment	Input-Output Variable, x_j	Minimum Feasible Fractional Capacity, x^L	Maximum Available Capacity, x^U
Anaerobic Digester, AD	x_0	0.60	1.00
Membrane Separator, MM1	x_1	0.60	1.12
Membrane Separator, MM2	x_2	0.60	1.12
Membrane Separator, MM3	x_3	0.60	1.12
Gas Turbine, GT1	x_4	0.60	1.20
Gas Turbine, GT2	x_5	0.60	1.20
Gas Turbine, GT3	x_6	0.60	1.20
Gas Turbine, GT4	x_7	0.60	1.20
Heat Recovery Steam Generator, HRSG	x_8	0.10	27.35
Water-Tube Boiler, WTB1	x_9	0.05	1.10
Water-Tube Boiler, WTB2	x_{10}	0.10	1.10
Biomass Dryer, DR	x_{11}	0.10	1.30
Cooling Tower, CT	x_{12}	0.10	1.88
Mechancial Chiller, MCH	x_{13}	0.60	39.60
High Pressure Steam Turbine, HST1	x_{14}	0.55	1.10
High Pressure Steam Turbine, HST2	x_{15}	0.55	1.10
High Pressure Steam Turbine, HST3	x_{16}	0.55	1.10
High Pressure Steam Turbine, HST4	x_{17}	0.55	1.10
Mid Pressure Steam Turbine, MST1	x_{18}	0.77	1.54
Mid Pressure Steam Turbine, MST2	x_{19}	0.77	1.54
Mid Pressure Steam Turbine, MST3	x_{20}	0.77	1.54

Table 7.3: Mass and Energy Balance for Technologies in Palm-based BES

	AD	MM1	MM2	MM3*	GT1	GT2	GT3	GT4*	HRSG
POME (kg/h)	-55,500.00								
Biogas (kg/h)	319.13	-159.57	-159.57	-159.57					
Biomethane (kg/h)		157.97	157.97	157.97	-105.31	-105.31	-105.31	-105.31	
Power (kW)		-47.87	-47.87	-47.87	416.30	416.30	416.30	416.30	
Flue Gas (kg/h)					526.57	526.57	526.57	526.57	-1,579.71
Released Flue Gas (kg/h)									1,579.71
Return Water (kg/h)									
Cooling Water (kg/h)									-1,671.84
Chilled Water (kg/h)									
EFB (kg/h)									
PMF (kg/h)									
Dried Biomass (kg/h)									
HPS (kg/h)									1,671.84
MPS (kg/h)									
LPS (kg/h)									

*Back-up Equipment

Table 7.3: (Continued)

	WTB1	WTB2*	DR	CT	MCH	HST1	HST2	HST3
POME (kg/h)								
Biogas (kg/h)								
Biomethane (kg/h)								
Power (kW)					-6.31	453.22	453.22	453.22
Flue Gas (kg/h)								
Released Flue Gas (kg/h)	32,558.01	32,558.01						
Return Water (kg/h)				-57,218.00				
Cooling Water (kg/h)	-39,268.05	-39,268.05		56,218.00	-279.00			
Chilled Water (kg/h)					1,000.00			
EFB (kg/h)			-16,875.00					
PMF (kg/h)			-9,245.30					
Dried Biomass (kg/h)	-11,950.80	-11,950.80	11,950.80					
HPS (kg/h)	39,268.05	39,268.05				-13,646.63	-13,646.63	-13,646.63
MPS (kg/h)						13,646.63	13,646.63	13,646.63
LPS (kg/h)			-12,814.88					

*Back-up Equipment

Table 7.3: (Continued)

	HST4*	MST1	MST2	MST3*	**Net Flow**
POME (kg/h)					-55,500.00
Biogas (kg/h)					0.00
Biomethane (kg/h)					0.00
Power (kW)	453.22	161.60	161.60	161.60	2,781.84
Flue Gas (kg/h)					0.00
Released Flue Gas (kg/h)					34,137.72
Return Water (kg/h)					-57,218.00
Cooling Water (kg/h)					14,999.11
Chilled Water (kg/h)					1,000.00
EFB (kg/h)					-16,875.00
PMF (kg/h)					-9,245.30
Dried Biomass (kg/h)					0.00
HPS (kg/h)	-13,646.63				0.00
MPS (kg/h)	13,646.63	-20,469.95	-20,469.95	-20,469.95	0.00
LPS (kg/h)		20,469.95	20,469.95	20,469.95	28,125.01

*Back-up Equipment

7.3.1 DSA

The DSA aims to determine if the BES design synthesised in Chapter 5 is capable of handling potential equipment failures. Using the conventional representation of the input-output model, a baseline IIM is developed. The equation below shows the formulation which represents the net flowrate of power (y_4, as per sequence in Table 7.3) for this case study;

$$-47.87*x_1 - 47.87*x_2 - 47.87*x_3 + 416.30*x_4 + 416.30*x_5 + 416.30*x_6 + 416.30*x_7 - 6.31*x_{13} + 453.22*x_{14} + 453.22*x_{15} + 453.22*x_{16} + 453.22*x_{17} + 161.60*x_{18} + 161.60*x_{19} + 161.60*x_{20} = y_4 \quad (7.3)$$

where x_{1-3}, x_{4-7}, x_{13}, x_{14-17} and x_{18-20} (as per sequence of streams in Table 7.3) are the operating capacities of membrane separators, gas turbines, mechanical chiller, high pressure steam turbines and medium pressure steam turbines respectively. With the baseline model, the DSA is performed. In this case study, the DSA introduces a failure scenario for high pressure steam turbine, HST3 at a given time of the operation (shown in Figure 7.5). Failure in HST3 is programmed into the baseline model as shown below;

$$x_{16} = 0 \quad (7.4)$$

Due to the adequate redundancy allocated in Chapter 5, back-up turbine HST4 is able to respond to the failure by starting up. This would allow the system to maintain a consistent operation and supply utilities to its clients despite experiencing equipment failure.

7.3.2 FOR Analysis

Following this, FOR analysis is performed to determine the FOR of the BES design. Based on the steps presented in Section 7.2.2, the FOR of the BES is determined and shown in Figure 7.6. The FOR suggests that the BES has sufficient operating capacity to deliver the intended seasonal demands shown in Table 7.1, hence validates its operability. As a result, the BES design from Chapter 5 can be recommended for construction as well as commissioning.

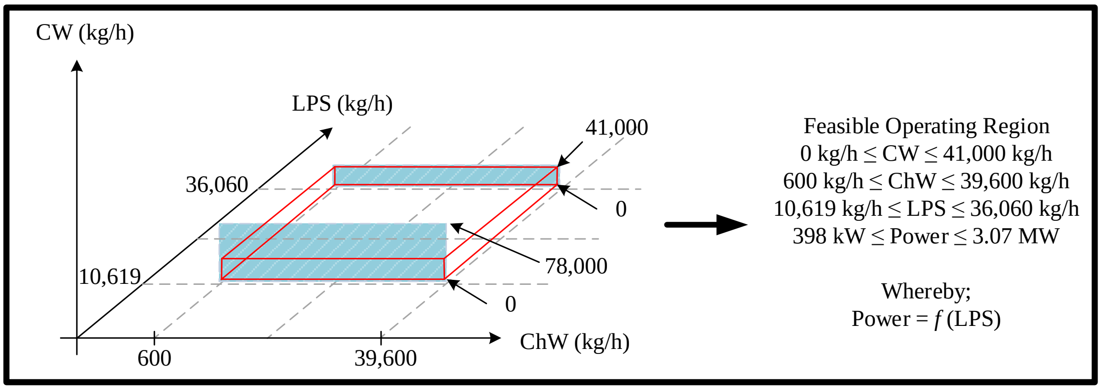

Figure 7.6: Identified Feasible Operating Range for Case Study

7.4 Summary

In Chapter 7, a systematic framework on Design Operability Analysis (DOA) is presented for a BES. The proposed framework consists of the DSA and the FOR analysis. In DSA, equipment failure scenarios are studied to determine if a synthesised BES design configuration is able to remain operable. The FOR analysis determines the inherent FOR of the synthesised BES. The FOR accounts for the interdependency between utilities produced and represents a range of net utility output a BES can deliver within its design and performance limitations. This range allows designers to recognise the true operating potential of the system and use it to analyse its performance for an intended seasonal energy demand. To illustrate the proposed framework, a palm BES design from Chapter 5 is used as a case study. Chapter 8 is directed toward extending the framework in Chapter 7 to Design Retrofit Analysis (DRA).

CHAPTER 8

SYSTEMATIC FRAMEWORK FOR DESIGN RETROFIT ANALYSIS (DRA) OF BIOMASS-BASED ENERGY SYSTEMS

8.1 Introduction

In Chapter 8, a systematic framework for Design Retrofit Analysis (DRA) of biomass-based energy system (BES). In the case where demand variations are present in future, DRA looks at what happens to the BES performance after years of operation and enable designers to determine it requires debottlenecking/retrofitting. The proposed framework extends the work in Kasivisvanathan et al. (2014) by incorporating disruption scenario analysis (DSA) and feasible operating range analysis (FORA). Unlike Chapter 7, the DSA and FORA is used in Chapter 8 to re-analyse an existing BES's capability of coping with equipment failure and its real-time feasible operating range respectively. By doing so, designers will be well informed to decide whether an existing system requires debottlenecking. In the case where a system requires debottlenecking, Chapter 8 provides a step-by-step procedure to debottleneck and retrofit procedures. To illustrate the proposed framework, a palm BES case study from Chapter 5 is extended in Chapter 8.

8.2 Systematic Framework for Design Retrofit Analysis (DRA)

As shown in Figure 8.1, the framework begins by adapting procedures from discussed in Chapter 7. The DSA from Chapter 7 is used in Chapter 8 to re-evaluate the real-time capability of the operating system to cope with failures. If the operating system is able to handle failures introduced, it can be analysed further in the next step. Similar to Chapter 7, the following step performs FORA on the existing BES. By performing the FORA, designers can re-analyse the real-time feasible operating range of the system. Once the FORA is performed, designers can determine if there is sufficient capacity within the overall system to meet the new energy demand variation. If there is adequate capacity, the existing system can be approved for operational adjustments. However, if there is no adequate capacity available, the existing system would need to be debottlenecked and retrofitted. The subsequent task is comprised of several sequential steps for a process-oriented debottlenecking. The sequential steps start by identifying possible bottlenecks. In general, when a single utility demand changes, all stream flowrates found in the system will result in an incremental change. On the other hand, change in multiple utilities will depend on the system network topology in determining the percentage change in all other stream flowrates. The incremental change is used to analyse the system for limitations in the current process specifications and configuration. This limitation in a BES leads to a process bottleneck. An equipment or process unit is considered a bottleneck when there are restrictions in feedstock and equipment specifications, insufficient energy supply, or sub-optimal operating conditions and equipment efficiencies that prevent satisfactory operation from being achieved.

Once the problematic process unit is located, the strategy for system debottlenecking depending on the nature of constraints involved. They may include sub-optimal operating conditions and equipment/process efficiency, insufficient throughput or required energy, and limited process unit design capacity. Altering operating conditions (i.e. pressure and temperature) or equipment/process efficiencies may be necessary where the process may benefit from such specialised modifications. On the other hand, changing unit throughputs and equipment specifications, as well as adequate supply of energy is a straightforward response to meeting demand variations. However, if there is no margin available for adjustment, input or raw materials can be purchased externally to meet the variations. Otherwise, additional equipment can be purchased to increase the overall system capacity to meet demand variations. Alternatively, process intensification strategies can be used (Baldea, 2015; Moulijn et al., 2008; Ponce-ortega et al., 2012). It is important to note that each step in Figure 1 will be limited only to one bottleneck process unit before moving to the next. For example, once debottlenecking is attempted by optimising process operating conditions, the entire network has to be ensured to be free from a similar limitation. Only then it is recommended to assess the design for the next criteria which is equipment and process efficiency, as shown in Figure 8.1. However, removal of one bottleneck may create a new bottleneck elsewhere in the system. Therefore, after each debottlenecking attempt, the system has to be re-analysed for the presence of any other limiting components or resources that imposes more bottlenecks. If there are no further bottlenecks identified, the system design is re-assessed with the FOR analysis. By doing so, designers will determine the new feasible operating range of the BES design. The new feasible operating range would decide whether the system design has sufficient capacity for the demand variations considered.

After analysing the feasible operating range, the system can be assessed for its associated potential risks. Note that there are a few essential risk and safety issues to be analysed. The risk involved in process or non-process hazards need to be assessed during the normal operations. Basic risk assessments that can be carried out include quantitative risk assessment (QRA), hazard operability study (HAZOP), and hazard identification analysis (HAZID) (MES, 2016). The risk associated to the design and layout available at this stage is analysed, quantified and rated. Typically, only if the entire system complies with legal safety standards and requirements after debottlenecking activities, should it be evaluated for economic feasibility. Otherwise, the system needs to incorporate appropriate design modifications, and thereafter re-analysed for any new process bottlenecks. In case there is no additional margin to revise the design modifications from the last improved solution, the demand variation introduced cannot be met. In such cases, it may be necessary to consider for a new BES design as an ultimate solution. This is an iterative process with an intention to ensure all safety criterions are met to proceed with economic feasibility study.

The economic feasibility based on benefit-cost analysis, BCA (or cost-benefit analysis, CBA in some applications) of the proposed modification is performed to determine the overall savings gained from changes in system to be compared against the additional investment for retrofit. If the benefit-cost ratio (BCR) value is greater than unity, i.e. 1, it implies that the benefits outweigh the costs involved. A minimum threshold BCR (typically greater than 1) can be established *a priori* to tailor for a design's economic preference in order to account for profit margins. In line with BCA, a secondary evaluation can also be done on the agreed capital budget for the project. In some project plans, any expansion funding is normally extracted from the estimated profits obtainable from system operation across a timeline. In cases where the total capital required falls below the budget, then the decision is made to design, construct and commission the system. However, if both BCR and/or capital budget limitations are not satisfied (i.e. BCR < 1 and/or Total Capital > Allocated Budget), the system once again needs to be assessed with proposed new design modifications, and re-analysed for any new process bottlenecks. It may happen that the proposed design modifications have to be rejected to opt for change in the entire design proposed. This is possible when there is no additional margin available to incorporate any new design modifications.

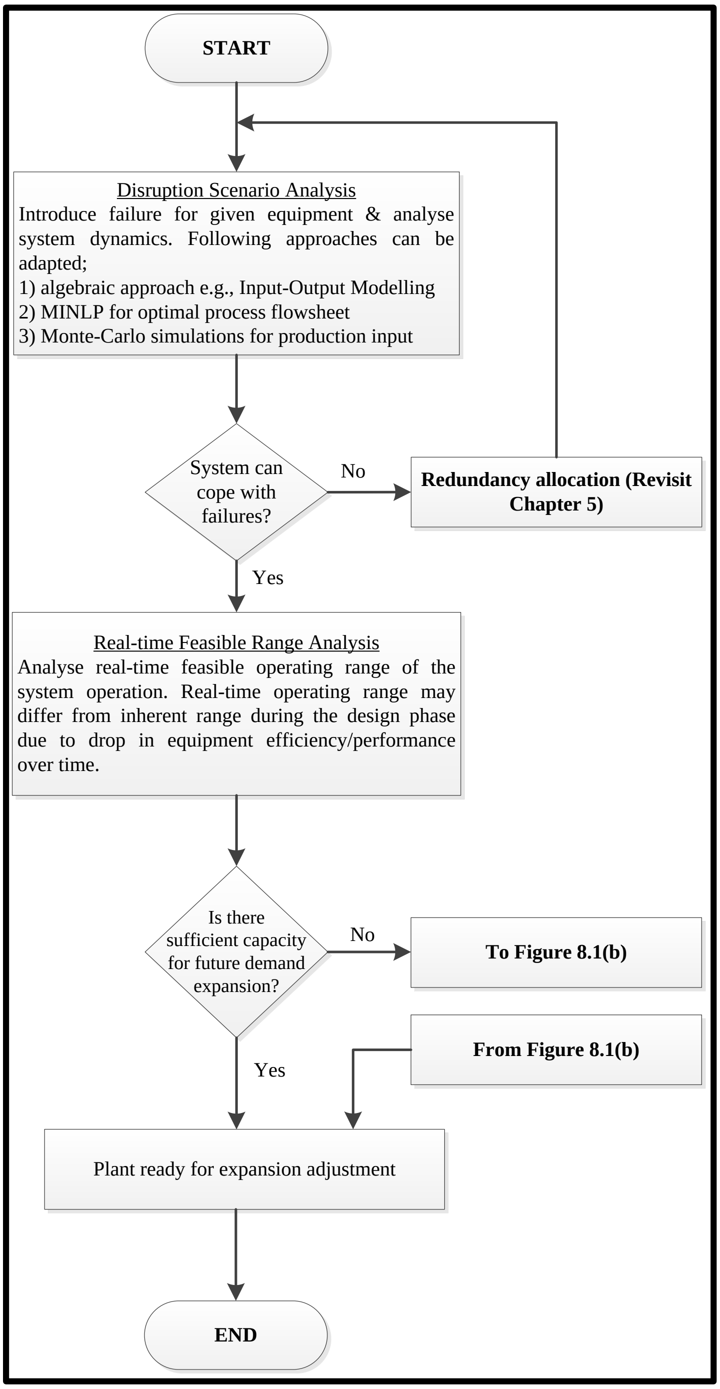

Figure 8.1: (a) Framework for Design Retrofit Analysis (DRA)

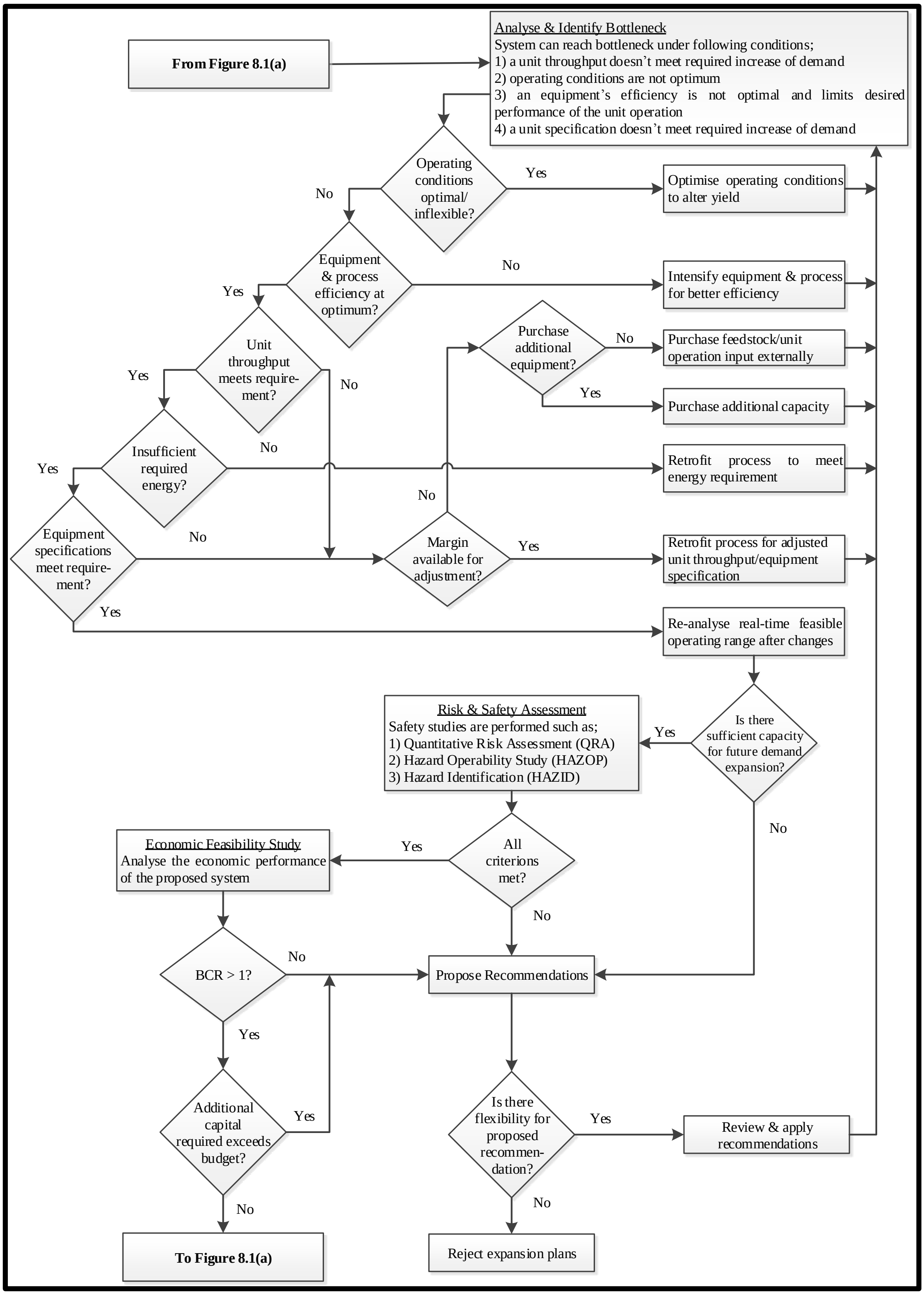

Figure 8.1: (b) (Continued)

The subsequent sections of this paper presents a case study to illustrate the proposed framework in Figure 8.1 in a more detailed manner. The model adapted in the case study is also provided to better appreciate the debottlenecking process. The case study give a stage by stage guideline in debottlenecking existing BES designs.

8.3 Case Study

In this case study, the framework in Figure 8.1 is used to address debottlenecking actions for the palm BES in Chapter 5, which is operational for a given period of time. Apart from this, it is assumed that after several years of operation, the BES is required to meet increased power demands from neighbouring facilities up to 4 MW. As such, this case study aims to identify possible bottlenecks within the palm BES and take necessary retrofit actions. Considering that the demand for power is increased from the previous operation, the flowsheet must be analysed for the possible bottlenecks before the increase in demand can be delivered in reality. To begin with debottlenecking attempts for any given BES design, an appropriate approach needs to be selected to model the designed state of the plant. This selection practice is important as it helps to recognise the complexity involved in the process modelling and hence determines the most suitable approach. The debottlenecking process for in this work adapts the inoperability input-output model (IIM) presented in Chapter 7. The IIM model for this case study is MILP in nature and is solved via LINGO v14 (Branch and Bound Solver) (LINDO Systems Inc., 2011) with Dell Vostro 3400 with Intel Core i5 (2.40GHz) and 4GB DDR3 RAM. Details of this model (e.g., codes, result scripts, CPU time, variables, integers, etc.) are included in Section A.5 of the Appendices.

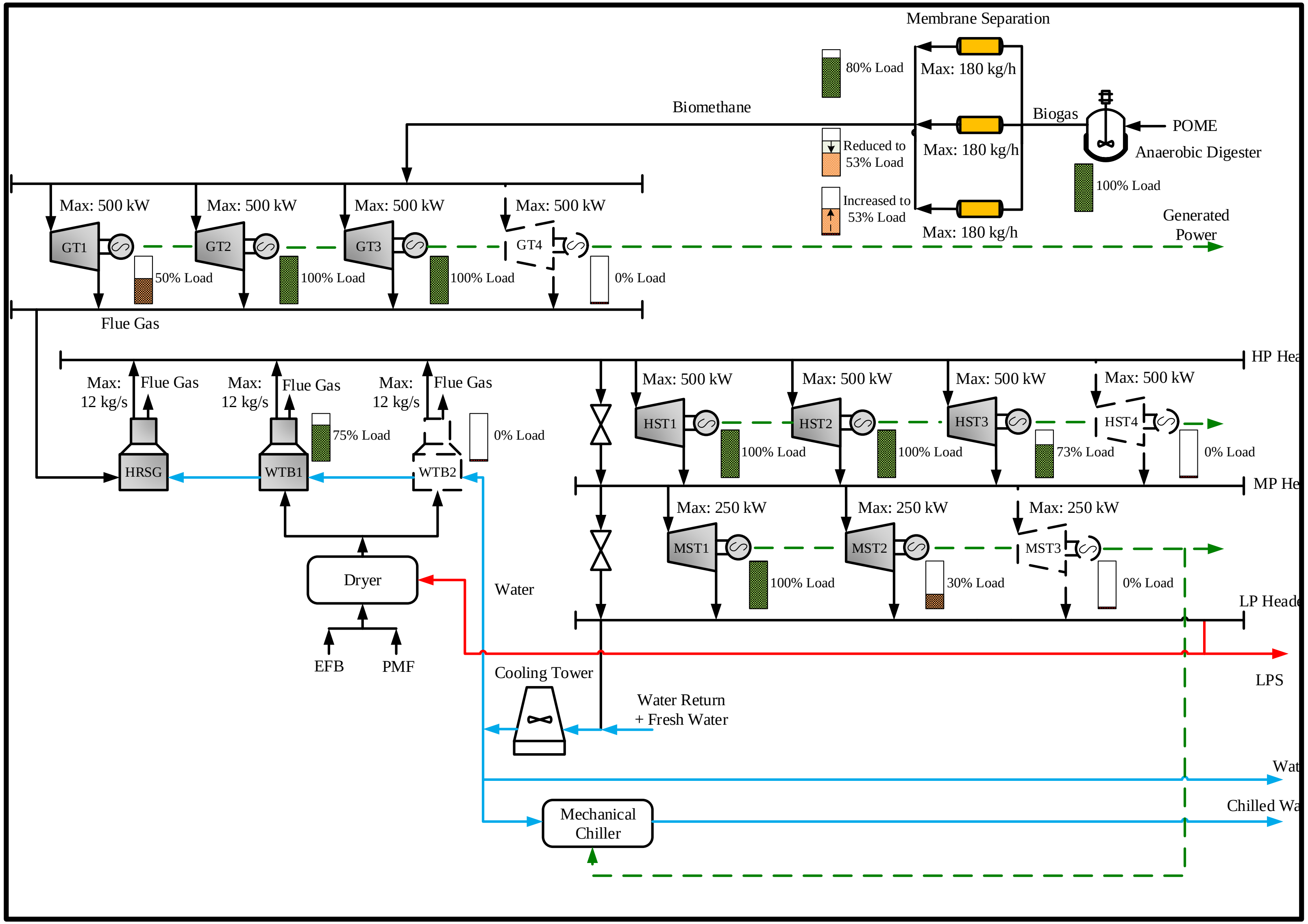

Figure 8.2: DSA for Case Study –Reduced Efficiency in Membrane Separator

Prior to debottlenecking, it is important to review the capability of the BES design to handle failures that may arise from dips in efficiency/performance over time. Such changes in equipment performances would certainly affect the real-time feasible operating range of the BES. If such changes in efficiencies are ignored, it may prove costly as decision making procedures would be made based on inaccurate representation of the BES performance. To address this issue, the framework in Figure 8.1 begins with the DSA. The DSA is carried out by first developing a baseline IIM model, similar to Chapter 7. The equation below shows the formulation which represents the net flowrate of bio-methane (y_3, as per sequence in Table 7.1 of Chapter 7) for this case study;

$$-157.97*x_1 - 157.97*x_2 - 157.97*x_3 - 105.31*x_4 - 105.31*x_5 - 105.31*x_6 - 105.31*x_7 = y_3 \tag{8.1}$$

where $x_{1\text{-}3}$ and $x_{4\text{-}7}$ (as per sequence of streams in Table 7.1 of Chapter 7) are the operating capacities of membrane separators and gas turbines respectively. With the baseline model, the DSA is performed. In this case study, the DSA assumes the separation efficiency of a membrane separator unit, MM2 has reduced after several years of operation (shown in Figure 8.2). Failure in MM2 is programmed into the baseline model as shown below;

$$x_2 = 0 \tag{8.2}$$

Based on the analysis, Figure 8.2 suggests that the BES is still adept to operate at its intended seasonal delivery despite experiencing reduced efficiency. This is followed by the FORA, whereby the real-time feasible operating range of the existing BES is determined. With the real-time feasible operating range, designers are allowed to make more well-informed decisions on whether to retrofit the existing BES. Figure 8.3 shows the resulting feasible operating range for the existing BES. Figure 8.3 suggests that there is a slight reduction in the range of power output from the BES, due to the drop in efficiency experienced by the membrane separator. The real-time feasible operating range indicates that the BES is unable to deliver 4 MW of power with its current configuration. As such, the BES must be analysed for bottlenecks and eliminated by making changes in design to cater for 4 MW power.

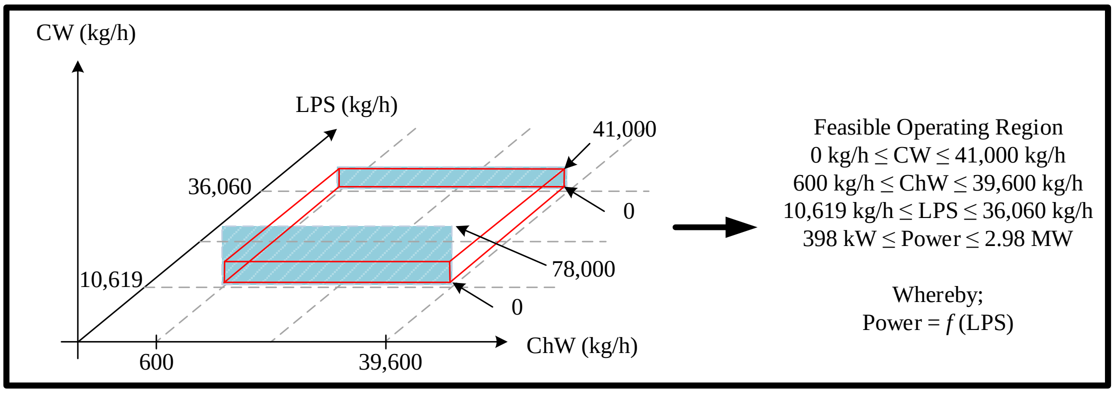

Figure 8.3: Identified Feasible Operating Range for Case Study

Based on the procedure presented in Section 8.2, process bottlenecks are identified and summarised in Table 8.1. The bottlenecks were identified by first tabulating the anticipated capacity increase in each equipment for the BES to deliver 4.0 MW power (see fifth column in Table 8.1). Following this, the anticipated capacities are then compared to existing maximum operating capacities shown in the fourth column of Table 8.1. The comparisons suggest that there are three process bottlenecks present in the BES, which are the anaerobic digester (AD), the biomass dryer (DR) and a high pressure steam turbine (HST).

Table 8.1: Identifying Bottlenecks

Equipment	Input-Output Variable, x_j	Minimum Feasible Capacity, x^L	Maximum Available Capacity, x^U	Anticipated Capacity Increase for 4MW, x_j	Bottleneck?	Comments
AD	x_0	0.60	1.00	1.00	**Yes**	
MM1	x_1	0.60	1.12	0.00	No	
MM2	x_2	0.60	1.12	1.12	No	Back-up capacity available
MM3	x_3	0.60	1.12	0.88	No	
GT1	x_4	0.60	1.20	1.20	No	Back-up capacity available
GT2	x_5	0.60	1.20	0.60	No	
GT3	x_6	0.60	1.20	0.00	No	
GT4	x_7	0.60	1.20	1.20	No	Back-up capacity available
HRSG	x_8	0.10	27.35	1.00	No	
WTB1	x_9	0.05	1.10	0.63	No	
WTB2	x_{10}	0.10	1.10	1.10	No	Back-up capacity available

Table 8.1: (Continued)

Equipment	Input-Output Variable, x_j	Minimum Feasible Capacity, x^L	Maximum Available Capacity, x^U	Anticipated Capacity Increase for 4MW, x_j	Bottleneck?	Comments
DR	x_{11}	0.10	1.30	1.73	**Yes**	Additional capacity required
CT	x_{12}	0.10	1.88	1.47	No	
MCH	x_{13}	0.60	39.60	1.00	No	
HST1	x_{14}	0.55	1.10	1.10	No	
HST2	x_{15}	0.55	1.10	1.10	No	
HST3	x_{16}	0.55	1.10	1.10	No	
HST4	x_{17}	0.55	1.10	1.79	**Yes**	Additional capacity required
MST1	x_{18}	0.77	1.54	1.08	No	
MST2	x_{19}	0.77	1.54	1.54	No	Back-up capacity available
MST3	x_{20}	0.77	1.54	0.77	No	

Since the IIM in this case study treats each unit operation as a "black box", the yield and efficiency of unit operations are assumed to be constant. It does not consider the change in thermodynamics of the processes involved and hence any internal change in conditions are neglected. This allows for the first two diamond boxes from the top of the framework in Figure 8.1 to be ignored in this case study. Thus, the first attempt of debottlenecking is to increase the total throughput of fresh fruit bunches in the palm oil mill. By doing so, the production of palm-based biomass from the palm oil mill can be raised to accommodate for the increase in demand. Nevertheless, it is assumed that there are no spare equipment within the palm oil mill here. It is only feasible to operate at a maximum of 100% capacity, i.e. the baseline state. In this case, the existing mill facilities limit this expansion as there is no additional capacity margin or spare facilities available. As such, it is only possible to purchase additional palm-based biomass externally to satisfy the new demand. This will require the computational difference of biomass given as follows:

EFB: 29,109.79 kg/h – 16,874.99 kg/h = 12,234.80 kg/h (8.3)

PMF: 15,948.37 kg/h – 9,245.30 kg/h = 6,703.07 kg/h (8.4)

This resolves the first debottlenecking step, and based on the framework, the BES can subsequently be debottlenecked to ensure sufficient access to required energy for the plant operation. However, as the BES is defined by a system of linear equations, the BES design for any new variation will readily take into account of sufficient supply of bioenergy from within itself. The IIM determines the total energy consumption in the network and thus allocates accordingly to fulfil its energy requirement. Therefore, moving down the framework to the fifth diamond box leads to increasing the unit maximum operating capacities for anaerobic digester, biomass dryer and high pressure steam turbine units as the next debottlenecking step. It will be a good measure to increase design capacities of these units with an additional of 50%, 50% and 110% respectively in order to accommodate for the new operation. These capacities are chosen specifically based on discrete sizes made available in the market by vendors. At this point, it is necessary for the BES to be re-analysed to ensure that it is free from other possible process bottlenecks. Thus far, all debottlenecking activities of the BES neither involved any change in process parameters nor equipment efficiencies. The alternatives used to debottleneck the BES are certainly under the influence of external factors such as external purchase of palm-based biomass feedstock and increase in process unit design capacity. Therefore, it can be ascertained that additional iterations through the framework would identify no more bottlenecks, allowing the new feasible operating range of the BES design to be re-analysed (via the FORA). The analysis yields a new feasible operating range as a result of additional changes in the BES design (Figure 8.4). Figure 8.4 affirms that the modified BES design is now equipped to deliver 4 MW power and can be assessed for associated potential risks. It is assumed in this case study that the safety studies do not reveal any critical concerns as there are no major modifications incorporated to the design of the BES at this stage. Following the safety assessment, the proposed design changes are then analysed for its economic feasibility.

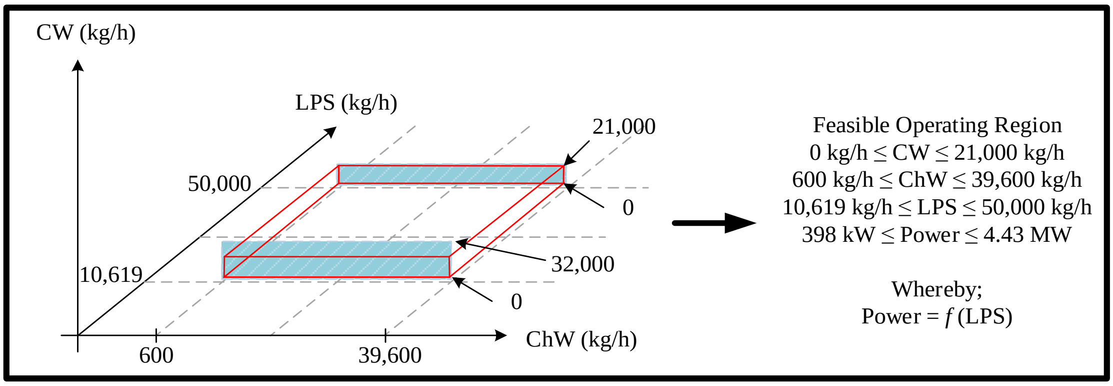

Figure 8.4: Feasible Operating Range of Proposed Retrofit

The economic feasibility of the proposed design is analysed over a year's period. As mentioned previously, the economic feasibility is evaluated via BCR. In this case study, *BCR* is a ratio of savings gained from changes in design to the additional capital cost for retrofit as shown in Equation 8.1.

$$BCR = \frac{\sum_{w} C_{w}^{\text{Stream}} y_{w}}{CAP^{\text{Add}}} \qquad (8.5)$$

where C_w^{Stream} is the unit cost of stream *w* and CAP^{Add} is the capital cost of additional equipment. CAP^{Add} is given by Equation 8.2 below:

$$CAP^{\text{Add}} = (\Sigma_j\, C_j^{\text{Cap}}\, x_j^{\text{U}}) \qquad (8.6)$$

where C_j^{Cap} is the annualised capital cost of process unit *j* with maximum operating capacity x_j^{U}. In this case study, savings gained from design changes are computed as the difference between income gained by the BES from supply additional power to the total cost of consuming of additional palm-based biomass feedstocks, i.e. EFB and PMF purchased externally. All costs of the palm-based biomass feedstocks along with the price of exported power are summarised in Table 8.2. Using the Equations 8.1 – 8.2, the proposed design yields an economic performance as shown in Table 8.3. As shown in Table 8.3, the BCR obtained is below zero (BCR < 0), which indicates that the proposed changes is not cost beneficial. In this case, Figure 8.1 suggests that alternative modifications should be considered for the BES and additional iterations through the framework must be performed.

Table 8.2: Price and Cost of Power and Palm-based Biomass

Stream, y_w	**Cost, C_w^{Stream} (US$)**
Exported Power (kW)	0.0714/kW
EFB (kg/h)	0.0060/kg
PMF (kg/h)	0.0220/kg
POME (kg/h)	-

Table 8.3: Economic Performance of Proposed BES Design

Economic Performance		
Cost of Additional Feedstock Consumption (US$/yr)		1,104,381.70
Additional Income Gained (US$/yr)		698,725.00
Additional Capital Costs (US$)		
Biomass Dryer	50% Capacity	90,000.00
High Pressure Steam Turbine	110% Capacity	90,549.00
Anaerobic Digester	50% Capacity	330,225.00
Annualising Factor (/yr)		0.13
CAP^{Add} (US$/yr)		66,400.62
BCR		**-6.11**

Alternatively, the BES can be modified by solely focusing on increasing the maximum operating capacity of the anaerobic digester. Similar to the previously propose design, it is necessary to purchase additional palm-based biomass externally to satisfy the new demand. This will require the computational difference of biomass given as follows:

EFB: 21,445.30 kg/h – 16,874.99 kg/h = 4,570.31 kg/h (8.7)

PMF: 11,749.23 kg/h – 9,245.30 kg/h = 2,503.93 kg/h (8.8)

POME: 88,800.00 kg/h – 55,500.00 kg/h = 33,300.00 kg/h (8.9)

This resolves the first debottlenecking step based on the framework. The anticipated capacity increase for the anaerobic digester would be 60% higher than its initial operation as shown in Table 8.4. This alternative design would eliminate the need to install additional a biomass dryer and higher pressure steam turbine as proposed previously. However, since design capacities in the market are available in discrete sizes, it is recommended that the anaerobic digester be increased to an additional 100% capacity. It can be established that no more bottlenecks are identified with additional iterations through the framework, allowing the new FOR of the BES design to be re-analysed via the FOR analysis. The analysis yields a new FOR as a result of additional changes in the BES design (Figure 5). Figure 8.5 affirms that the alternative BES design is able to deliver 4 MW power while maintaining its previous feasible ranges for other utilities. The alternative design then can be assessed for associated potential risks. It is assumed in this case study that the safety studies do not reveal any critical concerns as there are no major modifications required for the alternative design in this stage. Following the safety assessment, the alternative design is then analysed for its economic feasibility.

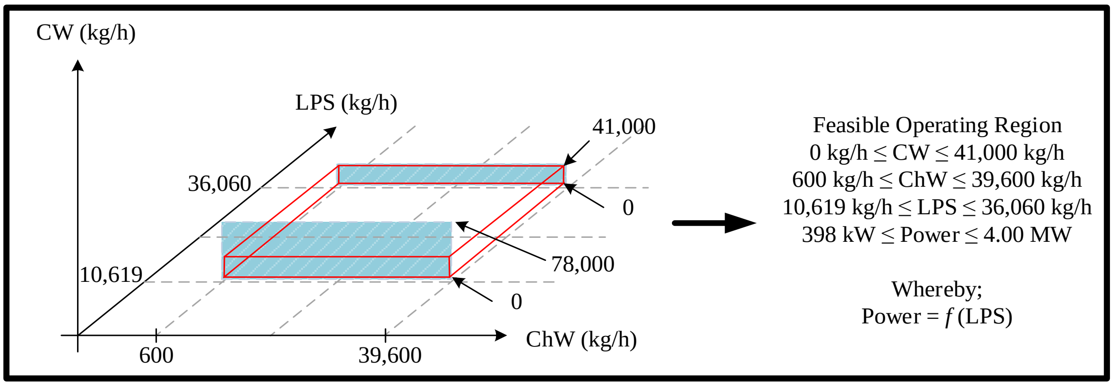

Figure 8.5: Feasible Operating Range for Alternative Design

Table 8.5 shows the economic performance of the alternative design. The results in Table 8.5 suggests that there is a significant improvement on the BCR value, whereby the BCR is greater than unity (1). This implies that the alternative design is a cost beneficial approach to retrofitting the BES. Through the analysis and debottlenecking procedures in Figure 8.1, the alternative BES design is economically feasible, and the decision can be made to proceed with corresponding retrofit actions and operational adjustments.

Table 8.4: Identifying Bottlenecks for Alternative Modification

Equipment	Input-Output Variable, x_j	Minimum Feasible Capacity, x^L	Maximum Available Capacity, x^U	Anticipated Capacity Increase for 4MW, x_j	Bottleneck?	Comments
AD	x_0	0.60	1.00	1.60	**Yes**	
MM1	x_1	0.60	1.12	1.12	No	Back-up capacity available
MM2	x_2	0.60	1.12	0.96	No	
MM3	x_3	0.60	1.12	1.12	No	Back-up capacity available
GT1	x_4	0.60	1.20	1.20	No	Full Capacity used
GT2	x_5	0.60	1.20	1.20	No	Full Capacity used
GT3	x_6	0.60	1.20	1.20	No	Full Capacity used
GT4	x_7	0.60	1.20	1.20	No	Full Capacity used
HRSG	x_8	0.10	27.35	1.60	No	
WTB1	x_9	0.05	1.10	0.17	No	
WTB2	x_{10}	0.10	1.10	1.10	No	Back-up capacity available

Table 8.4: (Continued)

Equipment	Input-Output Variable, x_j	Mininum Feasible Capacity, x^L	Maximum Available Capacity, x^U	Anticipated Capacity Increase for 4MW, x_j	Bottleneck?	Comments
DR	x_{11}	0.10	1.30	1.27	No	
CT	x_{12}	0.10	1.88	1.17	No	
MCH	x_{13}	0.60	39.60	1.00	No	
HST1	x_{14}	0.55	1.10	1.10	No	Back-up capacity available
HST2	x_{15}	0.55	1.10	0.58	No	
HST3	x_{16}	0.55	1.10	1.07	No	
HST4	x_{17}	0.55	1.10	1.10	No	Back-up capacity available
MST1	x_{18}	0.77	1.54	1.54	No	Back-up capacity available
MST2	x_{19}	0.77	1.54	0.00	No	
MST3	x_{20}	0.77	1.54	1.03	No	Back-up capacity available

Table 8.5: Economic Performance of Alternative Modification

Economic Performance			
Cost of Additional Feedstock Consumption (US$/yr)			412,541.60
Additional Income Gained (US$/yr)			698,725.00
Additional Capital Costs (US$)			
	Anaerobic Digester	100% Capacity	660,450.00
Annualising Factor (/yr)			0.13
CAP^{Add} (US$/yr)			85,858.50
BCR			**3.33**

8.4 Summary

In Chapter 8, a systematic framework for Design Retrofit Analysis (DRA) of BES was developed. In the proposed framework, DSA and FORA analysis is used to re-analyse an existing BES's capability of coping with equipment failure and its real-time feasible operating range respectively. The latter aspect allows temporal factors such as decline in process unit performance to be considered. Results of these analyses allows designers to decide whether an existing system requires debottlenecking. In the case where debottlenecking required, a step-by-step guide to debottleneck and retrofit a BES is provided. A palm BES case study from Chapter 5 is extended in this work to illustrate the proposed framework. In Chapter 9, a negotiation framework is presented to analyse the economic viability of a BES in an eco-industrial park.

CHAPTER 9

OPTIMISATION-BASED NEGOTIATION FRAMEWORK FOR ENERGY SYSTEMS IN AN ECO-INDUSTRIAL PARK

9.1 Introduction

Chapter 9 presents an optimisation-based negotiation framework for plants in an eco-industrial park (EIP). The framework combines the principles of rational allocation of benefits with the consideration of stability and robustness of the coalition to changes in cost assumptions by analysing its stability threshold. The stability threshold allows stakeholders to make informed managerial decisions concerning the current or future plant interactions in an EIP. The proposed framework is demonstrated using a palm oil eco-industrial park (PEIP) case study consisting of a biomass tri-generation system (BES), palm-based biorefinery (PBB) and palm oil mill (POM).

9.2 Problem Statement

The problem address in this work is stated as follows: A given set of plants ($u = 1, 2,\ldots, U$) are interested in forming a coalition within an EIP. However, as each plant contributes uniquely to the EIP, it is not clear as to how much a plant is entitled to receive from the collective cost savings obtained by the coalition. As such, Chapter 9 presents a systematic negotiation framework to determine the fair allocation of cost savings among participating plants based on their respective contributions toward the EIP. Following this, a stability analysis is conducted to investigate the stability threshold of the EIP coalition to in order to remain stable.

9.3 Optimisation-based Negotiation Framework

An optimisation-based negotiation framework for coalitions in EIPs is presented in Figure 9.1. The framework begins with interested plants discussing and proposing initial terms (e.g., the price of raw materials, energy and subsidies offered to one another, etc.) of interaction in the EIP coalition. These interactions are then mathematically formulated (discussed in the next section) and solved via a cooperative game theory model (Maali, 2009; Tan et al., 2015) to fairly allocate cost savings each plant deserves. Following this, an empirical stability analysis is used to investigate stability threshold of the coalition. The stability threshold is defined as the range of symbiosis costs (e.g., transportation, conveyor systems, etc.) each plant can absorb to maintain a stable coalition. A stable coalition is one that operates within a stability threshold that is feasible for all participating plants. The knowledge of these thresholds provides a rational starting point for stakeholders to analyses and engage in future coalitions in EIPs. Moreover, these thresholds give insight on the effect each plant's behaviour in the PEIP, especially when variations in symbiosis cost arise in the future. If the symbiosis costs for all plants fall within the stability threshold, the EIP coalition is considered stable and can be finalised. If not, it is possible to seek a mutual agreement among plants to share additional symbiosis cost based on the stability threshold. In the case where no agreement can be achieved, prior steps are revisited and the proposed framework in Figure 1 can be repeated until a mutually agreeable decision among all plants can be reached.

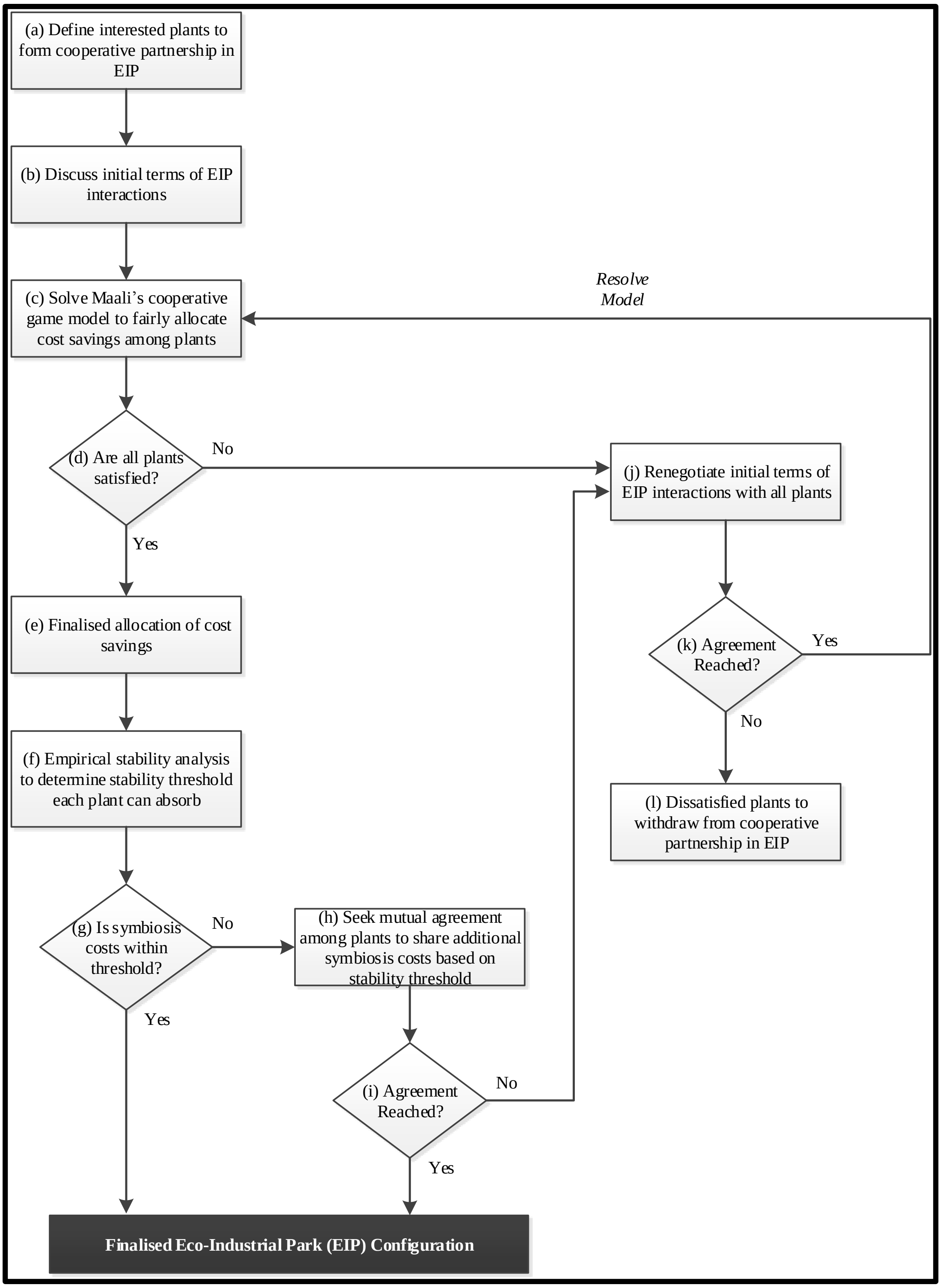

Figure 9.1: Optimisation-based Negotiation Framework for Cooperative Partnerships in EIPs

9.4 Mathematical Optimisation Formulation

The following sub-sections present mathematical formulations on the economic correlations, cost savings allocation and stability analysis of each plant *u* in an EIP.

9.4.1 Cost Savings Allocation

In this work, the cost savings allocation approach is divided into two sequential steps. The first step consists of determining the optimal configuration and computing corresponding costs savings for all possible coalitions in an EIP. Note that these cost savings are required as input for the second step and is obtained from repeated optimisations for each possible EIP coalition. The optimisation for a given EIP coalition is performed by maximising the sum of gross profits for plants *u*, as shown in Equation 9.1.

$$\text{Maximise} \quad GP^{\text{OVERALL}} = \sum_{u=1}^{U} GP_u \tag{9.1}$$

GP_u represents gross profit of each plant *u* in an EIP and is determined via Equation 9.2.

$$GP_u = \text{AOT} \times (\text{Product Revenue}_u - \text{Raw Material Cost}_u) \qquad \forall u \tag{9.2}$$

Note that AOT in Equation 9.2 represents the annual operating time in terms of hours per year (5,000 h/yr). The GP_u is determined based on the difference between the product revenue and raw material cost of each plant u. Meanwhile, the corresponding cost savings is calculated based on the amount of savings gained by a plant in an EIP as compared to operating as a stand-alone plant, importing material and utilities from external suppliers. As shown in Equation 9.3, the cost savings of plant u (CS_u) is calculated based on the difference in cost of a certain material in plant u from the EIP (C_u^{EIP}) compared to the cost of importing the same material from an externally (C_u^{Ext}).

$$CS_u = \mathrm{AOT} \times (C_u^{\mathrm{EIP}} - C_u^{\mathrm{Ext}}) \qquad \forall u \qquad (9.3)$$

The corresponding cost savings for all possible coalitions are then compiled and used as input data for the second step. The second step uses a cooperative game theory model (Maali, 2009) to fairly allocate cost savings among cooperative plants of in the EIP based on their respective contributions. This model is a mathematical programming-based approach proposed as an alternative to well-established concepts such as the Shapley value (Tan et al., 2015). In Maali's cooperative game theory model, z is a set of possible coalitions that can be formed among plants u (e.g., z =1, 2; 1, 3; 1, U). Equation 9.4 is included in the optimisation model to determine the weightage (C_u) of cost savings allocation (SA_u) for plant u.

$$\frac{1}{C_u} SA_u \geq \lambda \qquad \forall u \qquad (9.4)$$

The weightage is determined based on the incremental contribution of plant u in a coalition as shown in Equation 9.5, where CS_z represents the cost savings for a coalition while CS_{z-u} is the cost savings of a coalition without plant u CS_z and CS_{z-u} are obtained from the first step described in Equations 9.1 – 9.3.

$$C_u = \sum_z \left[CS_z - CS_{z-u}\right] \Big/ \sum_{u=1}^{U} CS_u \qquad \forall u \qquad (9.5)$$

Equation 9.6 is included in the model to determine SA_u for each plant u. In Equation 9.6, SA_u for each plant u must be greater than the savings attained individually by each plant u (CS_u).

$$SA_u \geq CS_u \qquad \forall u \qquad (9.6)$$

Meanwhile, Equation 9.7 is included to ensure that the sum of all SA_u is equal to the sum of CS_u.

$$\sum_{u=1}^{U} SA_u = \sum_{u=1}^{U} CS_u \qquad (9.7)$$

The objective function for this model is shown in Equation 9.8, where λ is maximised to give the optimum allocation of savings in Equation 9.4.

Maximise λ (9.8)

Once the optimum allocation is obtained, the stability analysis, which is to be discussed in the next section, is performed to analyse the stability threshold of the EIP coalition.

9.4.2 Stability Analysis

The stability analysis is conducted by measuring incremental investment return (IIR) as shown in Ng et al. (2015). The IIR measure is used to indicate if the incremental cost savings from the EIP is sufficient to offset the symbiosis cost required. The total symbiosis cost (SI^{OVERALL}) is determined by the summation of the symbiosis cost of participating plants u (SI_u) in the EIP (as shown in Equation 9.9).

$$SI^{\text{OVERALL}} = \sum_{u=1}^{U} SI_u \tag{9.9}$$

The total symbiosis savings (CS^{OVERALL}) is then determined by the summation of CS_u of the participating plants in the EIP as shown below.

$$CS^{\text{OVERALL}} = \sum_{u=1}^{U} CS_u \tag{9.10}$$

Following this, the overall distribution coefficient (DC^{OVERALL}) which is defined as the ratio of total symbiosis savings (CS^{OVERALL}) and the total symbiosis cost (SI^{OVERALL}) can be determined. DC^{OVERALL} is given as;

$$DC^{\text{OVERALL}} = \frac{CS^{\text{OVERALL}}}{SI^{\text{OVERALL}}} \tag{9.11}$$

The DC^{OVERALL} functions as a basis for fair or symmetrical distribution of cost savings among plants in an EIP. Ideally, each plant u would aim to achieve distributions equal to DC^{OVERALL}. This would mean that distribution of cost savings is symmetry, whereby each plant u can obtain the same allocation, making this an ideal status for plants u to strive for. However, in reality, the distributions of symbiosis savings and symbiosis cost of each plant u may deviate from DC^{OVERALL}. The deviation from ideal status is measured via the asymmetric distribution coefficient (Wang et al., 2013) of each plant u (ADC_u). ADC_u is written as:

$$ADC_u = \frac{DC_u}{DC^{\text{OVERALL}}} - 1 \qquad \forall u \qquad (9.12)$$

In Equation 9.12, DC_u represents the distribution coefficient of each plant u and is given as;

$$DC_u = \frac{SA_u}{SI_u} \qquad \forall u \qquad (9.13)$$

where SA_u is the cost savings allocated to plant u in Maali's cooperative game model. Note that ADC_u can be positive, negative or zero and is highly dependent on the cost savings associated with the symbiosis cost required for implementation of the EIP. Based on Equation 9.13, higher ADC_u represents higher symbiosis savings can be obtained and thus results in higher DC_u for plant u and vice versa. In the event where ADC_u is equal to 0, it means that plant u experiences no deviation of the distribution coefficient from the ideal status (when DC_u is equal to DC^{OVERALL}). In cases where ADC_u is negative, the symbiosis savings of plant u gained from EIP is below the ideal status. Meanwhile, if ADC_u = -1 (and DC_u = 0), plant u does not gain any savings from being in the EIP. In this respect, it would be desirable for ADC_u to be greater than 1 in order to encourage plants cooperation in the EIP (Wang et al., 2013).

To ensure a stable EIP coalition, ADC_u is bounded within maximum ($\mathrm{ADC}_u^{\max}$) and minimum ($\mathrm{ADC}_u^{\min}$) limits that are predefined by the participating plants, whereby $ADC_u \in (\mathrm{ADC}_u^{\min}, \mathrm{ADC}_u^{\max})$. As such, the coalition is considered stable if their respective ADC_u of each plant u is located within the predefined limits. On the other hand, if ADC_u falls out of the given range, the stability of the EIP will be compromised due to unreasonable distribution of cost savings (Wang et al., 2013). As mentioned by Wang et al. (2013), $\mathrm{ADC}_u^{\min}$ and $\mathrm{ADC}_u^{\max}$ might not be the same for all plants u, and the limits can be altered based on plants' requirements or company policies. It is imperative that all plants u negotiate and reach a consensus on the $\mathrm{ADC}_u^{\min}$ and $\mathrm{ADC}_u^{\max}$ limits to maintain a stable EIP coalition (Wang et al., 2013). In the case where the ADC_u of a particular plant falls outside the agreed range, stakeholders can consider to renegotiate and discuss the next step forward for the coalition. During negotiations, the affected plant(s) can suggest sharing some of the additional costs among cooperating plants in the EIP with respect to the agreed upon range. If no agreement can be achieved at this stage, plants can renegotiate the initial terms of the coalition and reallocate the cost savings. If this step still fails to yield an agreement, then the affected plant(s) can opt to withdraw from the coalition.

9.5 Case Study

In this case study, the PEIP consists of an existing palm oil mill (POM), a newly synthesised biomass-based energy system (BES) and palm-based biorefinery (PBB), each plant having its respective owner. The interaction between these plants is illustrated in Figure 9.2. As shown, the POM obtains fresh fruit bunches (FBBs) from the palm tree plantations as raw material. Meanwhile, POM requires utilities such as low pressure steam (LPS), cooling water, chilled water and power. These utilities can be purchased from the BES within the PEIP or from an external facility based on the respective purchasing prices listed in Table 9.1. Note that POM operation produces 11000.00 kg/h of crude palm oil (CPO) as the main product and empty fruit bunch (EFB), palm mesocarp fibre (PMF) and palm kernel shell (PKS) biomass as waste (with their respective compositions shown in Table 9.2). These biomass may be sold as raw materials to the BES and PBB at the given selling prices in Table 9.3. The BES and PBB can also purchase the biomass from external facilities at the prices listed in Table 9.3. POME produced by POM can be treated internally at a cost of 4.4800 US$/kg or outsourced to the BES at free of charge. Meanwhile, if EFBs are not utilised by BES or PBB, it would be disposed at the cost of 0.0023 US$/kg to transport the EFBs to the nearby plantation for mulching. Apart from that, PBB would require utilities such as medium pressure steam (MPS) and power for its operation. These utilities can be purchased from BES or from an external facility at higher prices (listed in Table 9.1). The potential end products of PBB are biofuels such as methanol (MeOH), dimethyl-ester (DME), biodiesel and bio-gasoline. These fuels are then sold to an external customer at the given prices in Table 9.4.

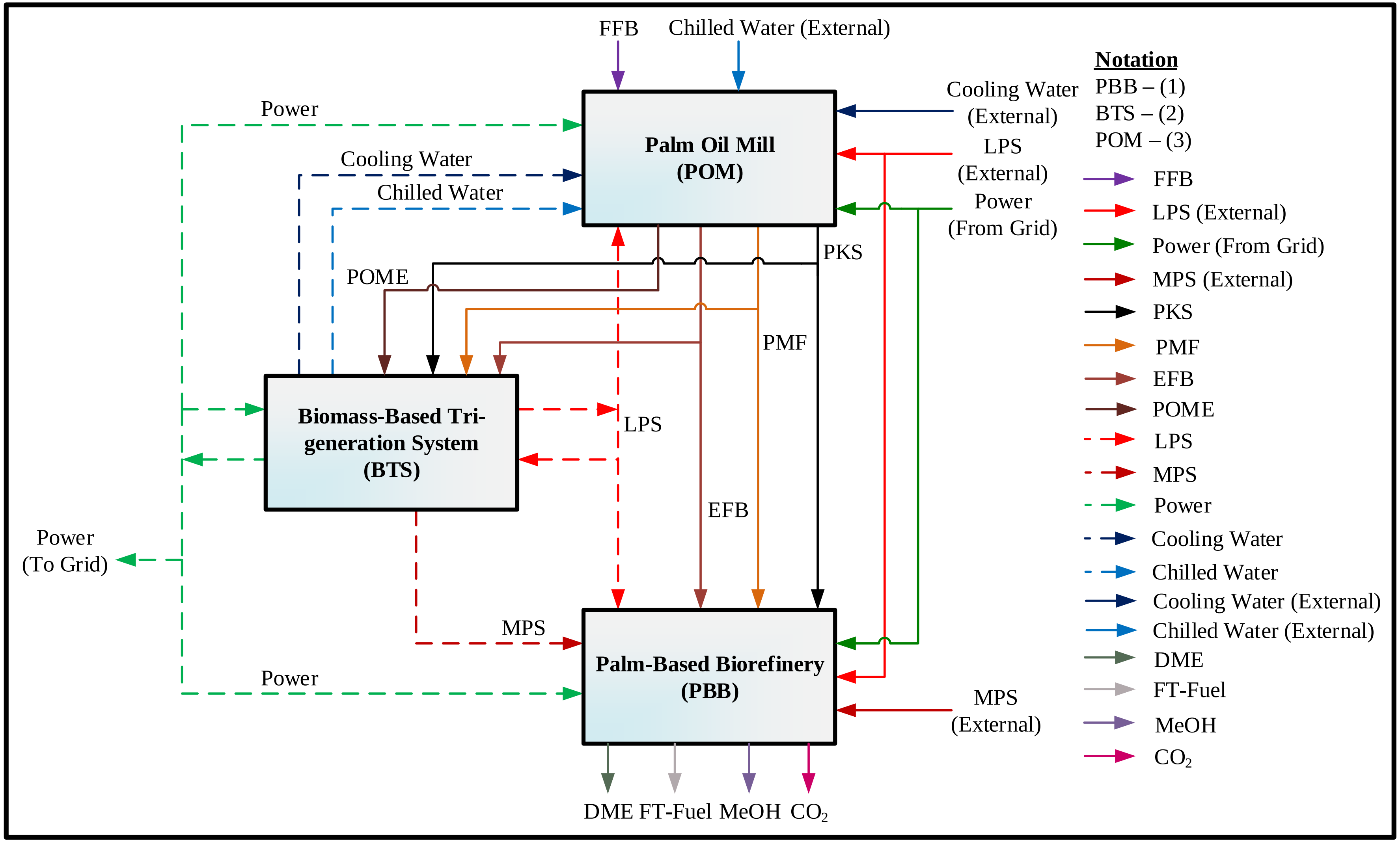

Figure 9.2: Block Diagram of PEIP in Case Study

Table 9.1: Utility Prices from BES and External Facility

Utility	BES (US$)	External (US$)
LPS	0.0184/kg	0.0207/kg
MPS	0.0460/kg	0.0483/kg
Cooling Water	0.00007/kg	0.000092/kg
Chilled Water	0.00046/kg	0.0007/kg
Power	0.0667/kWh	0.0897/kWh

Table 9.2: Composition of Available Palm-based Biomass

Raw Materials *i*	Component *q*	Composition θ_{iq} (%)
EFB	Cellulose	13
	Hemi-Cellulose	12
	Lignin	8
	Water	65
	Ash	2
PMF	Cellulose	21
	Hemi-Cellulose	19
	Lignin	15
	Water	40
	Ash	5
PKS	Cellulose	16
	Hemi-Cellulose	17
	Lignin	39
	Water	23
	Ash	4

Table 9.3: Material Prices from POM and External Facility

Material	POM (US$/kg)	External (US$/kg)
CPO	0.6900	-
EFB	0.0046	0.0069
PMF	0.0161	0.0184
PKS	0.0373	0.0414

Table 9.4: Material Prices from PBB

Material	**Selling Price (US$/kg)**
DME	0.4740
Biodiesel	0.1220
Biogasoline	0.2420
MeOH	0.8050

Based on data in Tables 9.1 – 9.4, superstructures are developed for BES and PBB as shown in Figures 4.6 (from Chapter 4) and 9.3 respectively. These superstructures enumerate several alternative technologies available for selection. These alternatives are mathematically modelled, allowing for quantitative screening and optimisation based on their gross profit. Meanwhile, the existing POM is described using an input-output model (Figure 4.4 from Chapter 4) as presented in Kasivisvanathan et al. (2012). Detailed mathematical formulations for BES, PBB and POM are included in Section A.6 of the Appendices. Conversion data are acquired from fundamental engineering calculations/references as shown in included in Table 4.7 (from Chapter 4) and Tables 9.5 – 9.6. Mathematical models developed for this case study are solved via LINGO v14 (Branch and Bound Solver) (LINDO Systems Inc., 2011) with Dell Vostro 3400 with Intel Core i5 (2.40GHz) and 4GB DDR3 RAM. Details of the mathematical model (e.g., codes, result scripts, CPU time, variables, integers, etc.) are presented in Section A.6 of the Appendices.

Table 9.5: Conversions for Technologies Considered in POM for Case Study

Technology	Conversions	Inlet	Product/ By-Product
Palm Oil Mill (POM)	FFB Requirement = 5 kg/ kg CPO	FFB	CPO
	LPS Requirement = 1.875 kg/ kg CPO	LPS (3 bar, 134°C)	EFB
	Cooled Water Requirement = 1 kg/ kg CPO	Cooled Water	PMF
	Chilled Water Requirement = 1000 kg/h	Chilled Water	PKS
	Power Requirement = 0.0575 kW/ kg CPO	Power	POME
	EFB = 1.125 kg/ kg CPO		
	PMF = 0.625 kg/ kg CPO		
	PKS = 0.3125 kg/ kg CPO		
	POME = 3.7 kg/ kg CPO		

Table 9.6: Conversions for Technologies Considered in PBB for Case Study

Technology	Conversions	Inlet	Product/ By-Product
Gasifier (30 bar, 350^{0}C)	0.03 kg H_2/kg Cellulose	Dried Palm Biomass	Syngas (30 bar, 350^{0}C)
	0.03 kg H_2/kg Hemi-Cellulose	Air	
	0.067 kg H_2/kg Lignin		
	0.649 kg CO/kg Cellulose		
	0.649 kg CO/kg Hemi-Cellulose		
	0.989 kg CO/kg Lignin		
	0.389 kg CO_2/kg Cellulose		
	0.389 kg CO_2/kg Hemi-Cellulose		
	0.98 kg CO_2/kg Lignin		
	0.082 kg CH_4/kg Cellulose		
	0.082 kg CH_4/kg Hemi-Cellulose		
	0.034 kg CH_4/kg Lignin		
	0.243 kg O_2/kg Cellulose		
	0.243 kg O_2/kg Hemi-Cellulose		
	1.42 kg O_2/kg Lignin		
Reformer	0.31875 kg H_2/kg CH_4	Syngas (from Gasifier)	Conditioned Syngas
(To convert CH_4 to H_2 and CO)	1.4875 kg CO/kg CH_4	MP Steam (20 bar, 284^{0}C)	
	Steam Requirement = 3.0375 kg /kg CH_4		

Table 9.6: (Continued)

Water Gas Shift Reactor (To convert CO to H_2 and CO_2)	0.0714 kg H_2/kg CO 1.571 kg CO_2/kg CO Steam Requirement = 3.0375 kg /kg CH_4	Syngas (from Reformer) MP Steam (20 bar, 284^{0}C)	Conditioned Syngas
Biomass Dryer	Outlet Moisture Content (wt%) = 10 Steam Consumption = 0.979 kg/ Water Removed	Wet Palm Biomass	Dried Palm Biomass
Amine Scrubbing	0.9994 kg Syngas/ kg Raw Syngas 0.998 kg Syngas/ kg Raw CO_2 Power Required = 0.14 kWh^2/kg Syngas	Syngas CO_2	Purified Syngas Separated CO_2
PSA	0.98 kg Syngas/ kg Raw Syngas 0.98 kg Syngas/ kg Raw CO_2 Power Required = 0.3 kWh^2/kg Syngas	Syngas CO_2	Purified Syngas Separated CO_2
Membrane Separation	0.99 kg Syngas/ kg Raw Syngas 0.98 kg Syngas/ kg Raw CO_2 Power Required = 0.3 kWh^2/kg Syngas	Syngas CO_2	Purified Syngas Separated CO_2

Table 9.6: (Continued)

Fischer-Tropsch Process	Biogasoline = 0.36 kg/ kg Purified Syngas Biodiesel = 0.24 kg/ kg Purified Syngas H_2/CO Ratio Requirement = 2	Purified Syngas	Biogasoline Biodiesel
Methanol Synthesis	Methanol = 0.937 kg/ kg Purified Syngas H_2/CO Ratio Requirement = 2	Purified Syngas	Methanol
DME Synthesis	DME = 0.28673 kg/ kg Purified Syngas H_2/CO Ratio Requirement = 2	Purified Syngas	DME

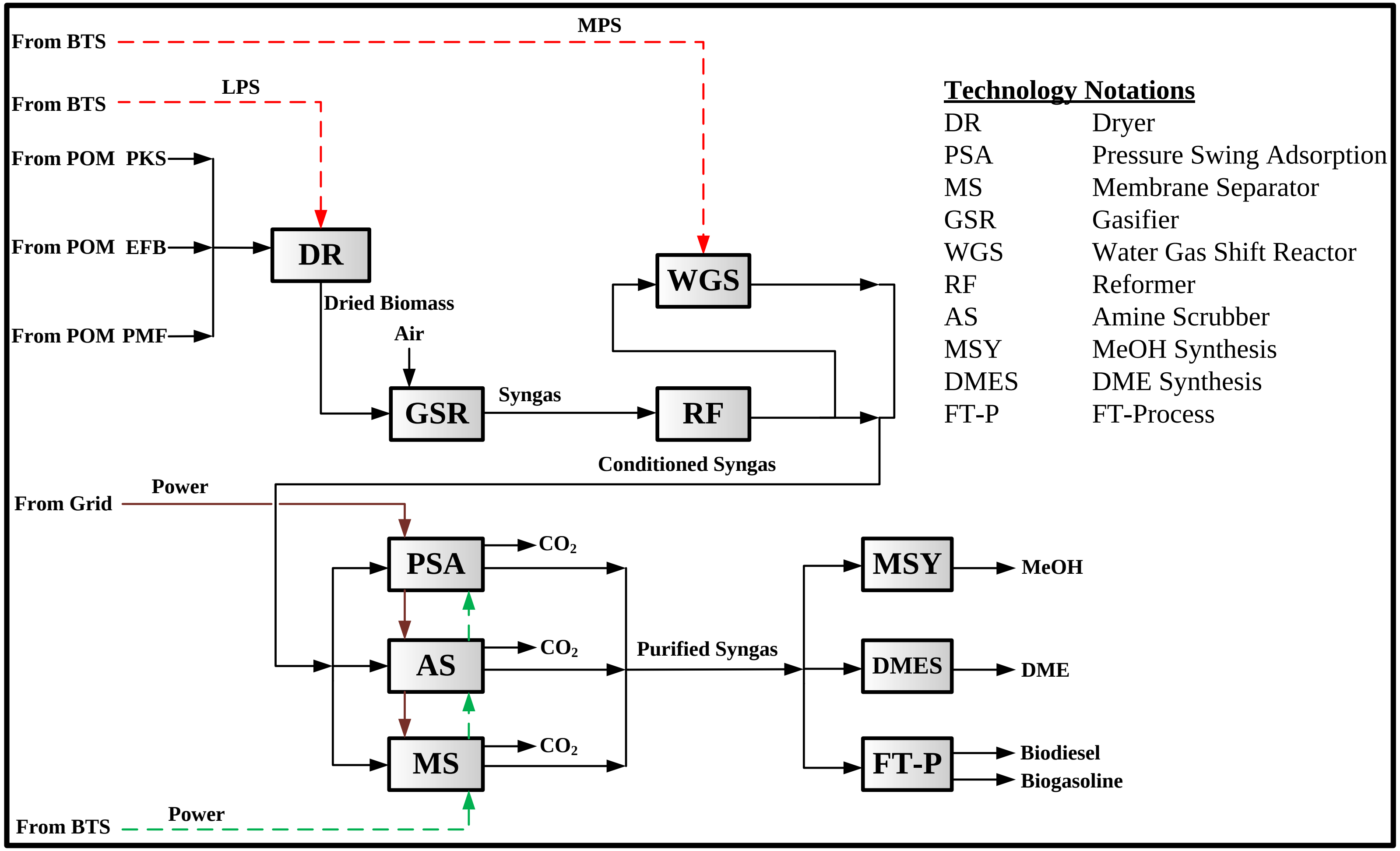

Figure 9.3: Superstructure for PBB in Case Study

9.5.1 Cost Savings Allocation

Following to the proposed approach, the cost savings of each possible coalition in the PEIP is to be computed. These cost savings are obtained by considering five different scenarios as shown in Table 9.7. In Scenario 1, GP^{OVERALL} is maximised and the optimised result of GP^{OVERALL} is determined as US$ 43,800,000. The corresponding cost savings for BES, PBB and POM are determined as US$ 400,000, US$ 200,000 and US$ 900,000 respectively. For Scenario 2, economic transactions between BES and POM are assumed to be waived by both parties. For instance, energy produced by BES can be supplied to POM at waived costs since both plants are in coalition. Similarly, palm-based biomass from the POM can be supplied to BES with no charges. GP^{OVERALL} of Scenario 2 is determined as US$ 43,800,000 while the total savings of POM and BES is US$ 4,100,000. In Scenario 3, the coalition assumes that economic transactions between PBB and POM are subsidized. The GP^{OVERALL} for Scenario 3 is then determined as US$ 43,800,000 while the total savings of PBB and POM is US$ 1,600,000. Similar with the previous scenarios, Scenario 4 assumes economic transactions between BES and PBB are subsidized. The maximum GP^{OVERALL} of this scenario is determined as US$ 43,800,000. The total savings of BES and PBB is determined as US$ 1,200,000. Lastly, Scenario 5 considers a coalition between all three plants. GP^{OVERALL} is determined as US$ 43,800,000 and the total savings for all three plants is US$ 5,400,000.

Table 9.7: Scenarios Studied in Case Study

Scenario	Description of Scenario
1	No coalition within PEIP
2	Coalition between BES and POM
3	Coalition between PBB and POM
4	Coalition between BES and PBB
5	Coalition between all three plants

Following this, the Maali's cooperative game model is formulated as shown in Equations 9.14 – 9.23. Note that Equations 9.14 – 9.16 are formulated based on the generic representation in Equation 9.4. Meanwhile, Equations 9.17 – 9.19 and 9.20 – 9.22 are formulated according to Equation 9.5 and Equation 9.6 respectively. Lastly, Equation 9.23 is formulated in accordance to Equation 9.7. Note also that in this case study, index u = 1 represents BES while u = 2, u = 3 represent PBB and POM respectively.

$$\left(1/C_1\right)SA_1 \geq \lambda \tag{9.14}$$

$$\left(1/C_2\right)SA_2 \geq \lambda \tag{9.15}$$

$$\left(1/C_3\right)SA_3 \geq \lambda \tag{9.16}$$

$$C_1 = \left(\mathrm{CS}_{123} - \mathrm{CS}_{23} + \mathrm{CS}_{12} - \mathrm{CS}_2 + \mathrm{CS}_{13} - \mathrm{CS}_3 + \mathrm{CS}_1\right)/\mathrm{CS}_{123} \tag{9.17}$$

$$C_2 = \left(\mathrm{CS}_{123} - \mathrm{CS}_{13} + \mathrm{CS}_{12} - \mathrm{CS}_1 + \mathrm{CS}_{23} - \mathrm{CS}_3 + \mathrm{CS}_2\right)/\mathrm{CS}_{123} \tag{9.18}$$

$$C_3 = \left(\mathrm{CS}_{123} - \mathrm{CS}_{12} + \mathrm{CS}_{13} - \mathrm{CS}_1 + \mathrm{CS}_{23} - \mathrm{CS}_2 + \mathrm{CS}_3\right)/\mathrm{CS}_{123} \tag{9.19}$$

$$SA_1 \geq \mathrm{CS}_1 \tag{9.20}$$

$$SA_2 \geq \mathrm{CS}_2 \tag{9.21}$$

$$SA_3 \geq \mathrm{CS}_3 \tag{9.22}$$

$$SA_1 + SA_2 + SA_3 = \mathrm{CS}_{123} \tag{9.23}$$

In order to solve the model formulated, input values of CS_1, CS_2, CS_3, CS_{13}, CS_{23}, CS_{12} and CS_{123} must be obtained. These input values are obtained from Scenarios 1 – 5 considered earlier. As shown in Table 9.8, the corresponding cost savings for the BES, PBB and POM in Scenario 1 are taken as CS_1, CS_2 and CS_3 respectively. Meanwhile, the total cost savings in Scenarios 2 – 5 are taken as CS_{13}, CS_{23}, CS_{12} and CS_{123} respectively. With these values, the allocation problem is solved by maximising λ as shown in Equation 9.8.

The results are summarised in Table 9.9 while the resultant PEIP configuration is shown in Figure 9.4. In addition, Figure 9.5 illustrates the synthesised configuration of the BES and PBB respectively. The allocation of savings SA_1, SA_2 and SA_3 are determined as US\$ 2,100,000 (38%), US\$ 800,000 (14%) and US\$ 2,600,000 (48%) respectively. These values are then utilised in the next section to analyse the stability threshold of the coalition.

Table 9.8: Input for Maali's Cooperative Game Model in PEIP Case Study

CS_z	(US$/yr)
CS_1	400,000
CS_2	200,000
CS_3	900,000
CS_{13}	4,100,000
CS_{23}	1,600,000
CS_{12}	1,200,000
CS_{123}	5,400,000

Table 9.9: Savings Allocation between BES, PBB and POM in PEIP

	Savings Allocation, SA_u (US$/yr)	**Allocation (%)**
Plant 1 (BES)	2,100,000	38
Plant 2 (PBB)	800,000	14
Plant 3 (POM)	2,600,000	48
Total	**5,500,000**	**100**

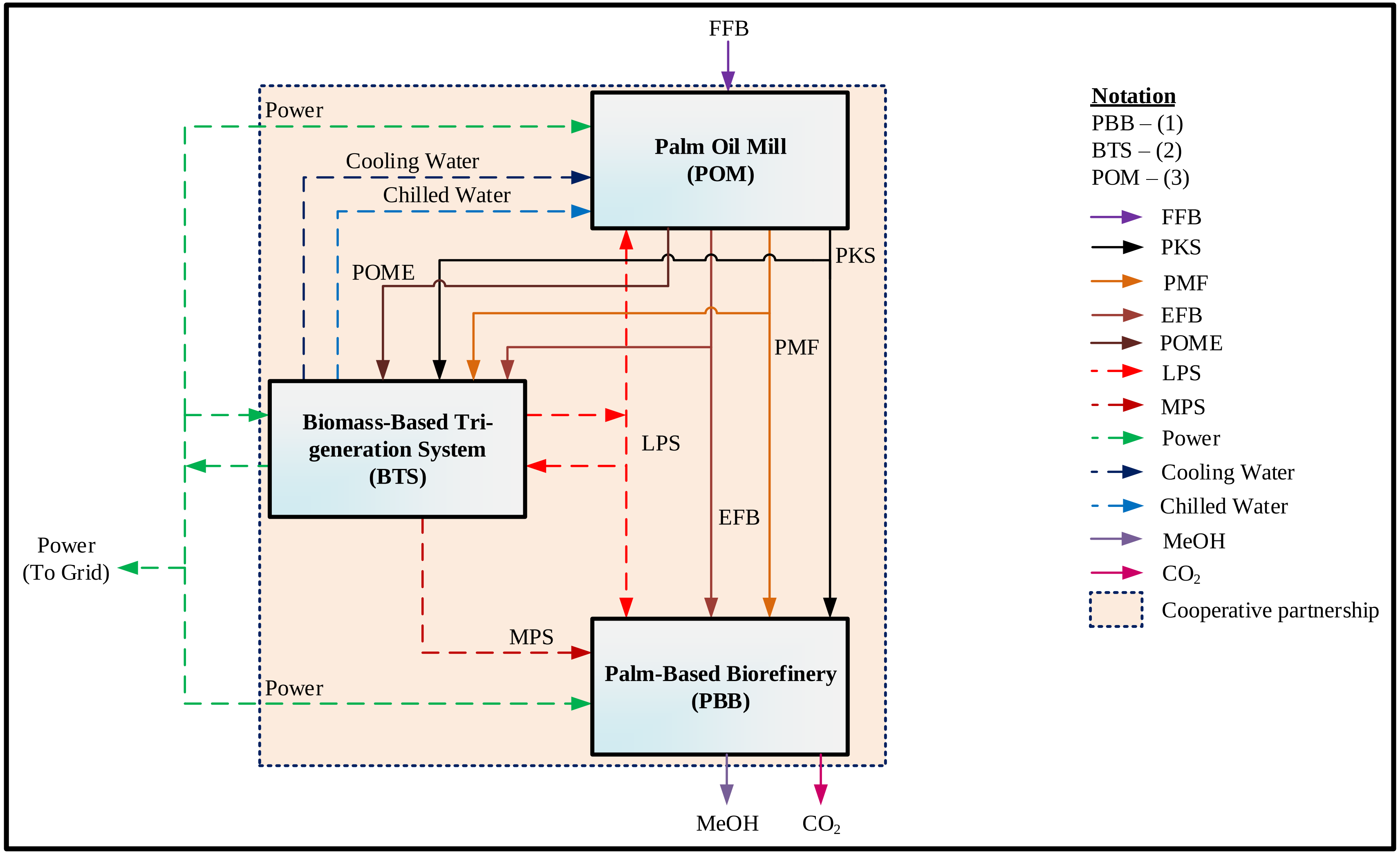

Figure 9.4: Final PEIP Diagram

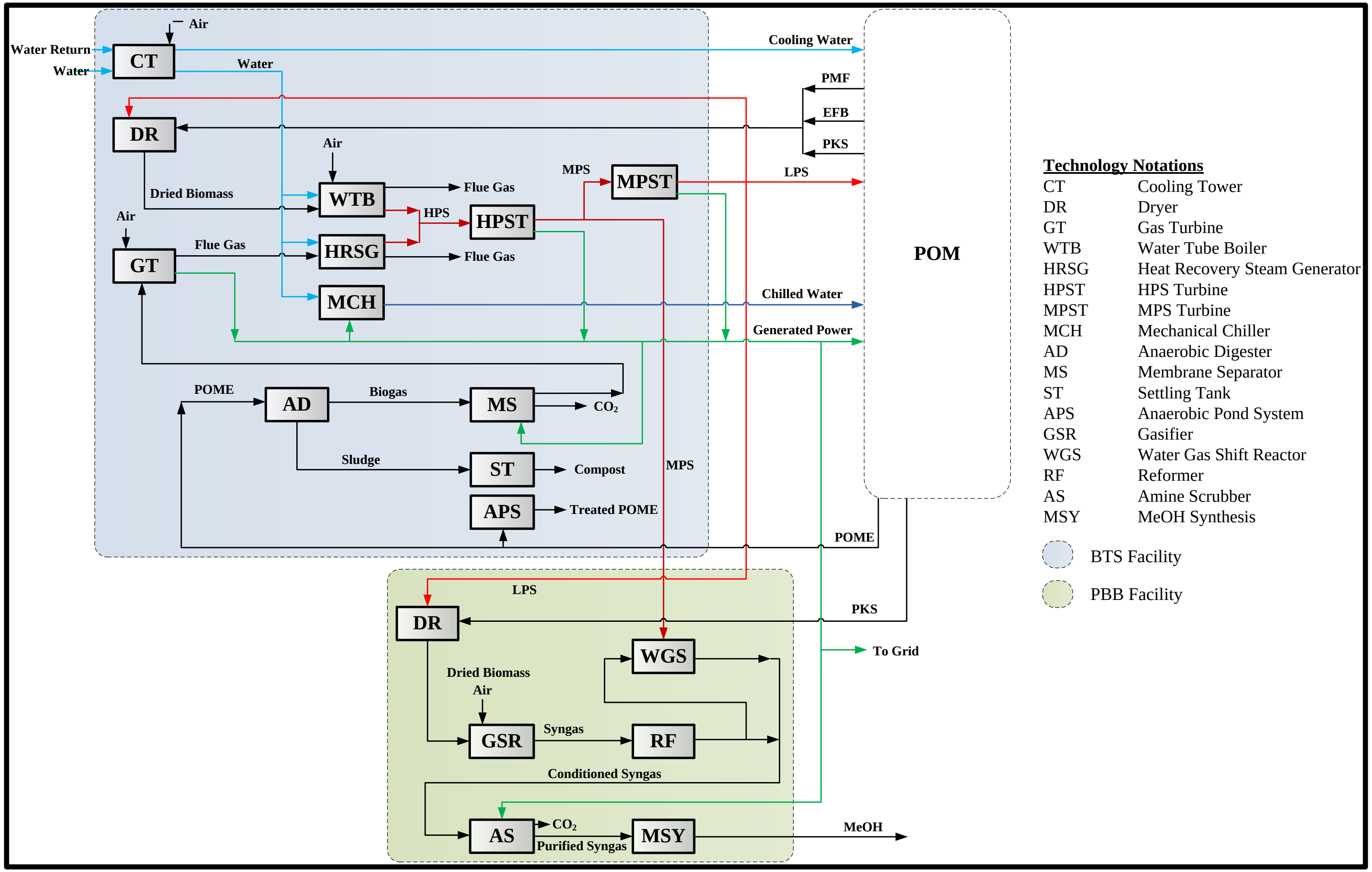

Figure 9.5: Synthesised PEIP Configurations

9.5.2 Stability Analysis

For the stability analysis, this case study assumes that the symbiosis cost of a plant *u* (SI_u) is given as a fraction (cf_u) of its raw material costs (shown in Equation 9.24). As such, the stability threshold is determined by investigating the range in which values of cf_u would provide a stable PEIP coalition. Moreover, it is assumed that all plants agree that the PEIP coalition is considered stable only when ADC_u of each plant is within –0.5 to 0.5. Following this, the stability analysis is formulated as shown in Equations 9.25 – 9.33. Equations 9.23 – 9.33 are formulated based on the generic representation presented in Equations 9.9 – 9.13.

$$SI_u = cf_u \times \text{Raw Material Cost}_u \qquad \forall u \tag{9.24}$$

$$SI^{\text{OVERALL}} = SI_1 + SI_2 + SI_3 \tag{9.25}$$

$$CS^{\text{OVERALL}} = CS_1 + CS_2 + CS_3 \tag{9.26}$$

$$DC^{\text{OVERALL}} = \frac{CS^{\text{OVERALL}}}{SI^{\text{OVERALL}}} \tag{9.27}$$

$$ADC_1 = \frac{DC_1}{DC^{\text{OVERALL}}} - 1 \tag{9.28}$$

$$ADC_2 = \frac{DC_2}{DC^{\text{OVERALL}}} - 1 \tag{9.29}$$

$$ADC_3 = \frac{DC_3}{DC^{\text{OVERALL}}} - 1 \tag{9.30}$$

$$DC_1 = \frac{SA_1}{SI_1} \tag{9.31}$$

$$DC_2 = \frac{SA_2}{SI_2} \tag{9.32}$$

$$DC_3 = \frac{SA_3}{SI_3} \tag{9.33}$$

Prior to determining the stability threshold, a decision hierarchy is first defined for the PEIP coalition. The decision hierarchy describes which plant in the PEIP coalition has a high influence on operational decisions. Based on Figure 9.2, it is found that operational decisions in the POM would outweigh the decisions in the BES and PBB as it is the sole provider of raw materials in the coalition. If any variations or disturbances are experienced in the POM, it would cause a “ripple” effect toward BES and PBB operations and subsequently destabilizing the EIP coalition. In that respect, the POM is placed on the top of the decision hierarchy as shown in Figure 9.6. Based on Figure 9.6, the stability threshold is determined by investigating the behavior of cf_1 and cf_2 values with respect to cf_3 as shown in Figures 9.7 – 9.9. In Figure 9.7, the range of stability for fractions cf_1 and cf_2 is investigated empirically when cf_3 = 20%. The verticals lines shown in the plot represent the range in which cf_1 values give a stable EIP when cf_2 is gradually increased. Meanwhile, the horizontal lines indicate the common region of stability of cf_1 for different values of cf_2. Similarly, results for cf_3 = 25% and cf_3 = 30% are shown in Figures 9.8 and 9.9 respectively. Based on the results, the resultant common region of stability shown below is the stability threshold for the PEIP coalition;

$$37\% \leq cf_1 \leq 46\%$$

$$10\% \leq cf_2 \leq 30\%$$

$$20\% \leq cf_3 \leq 25\%$$

If the symbiosis cost of one (or more) plant(s) fall outside the abovementioned stability threshold, the stability of the PEIP coalition is compromised and further action must be taken as stipulated in Figure 9.1.

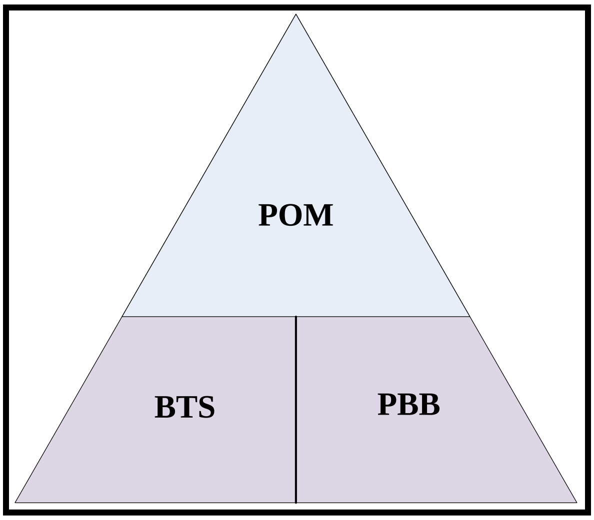

Figure 9.6: Decision Hierarchy of PEIP Case Study

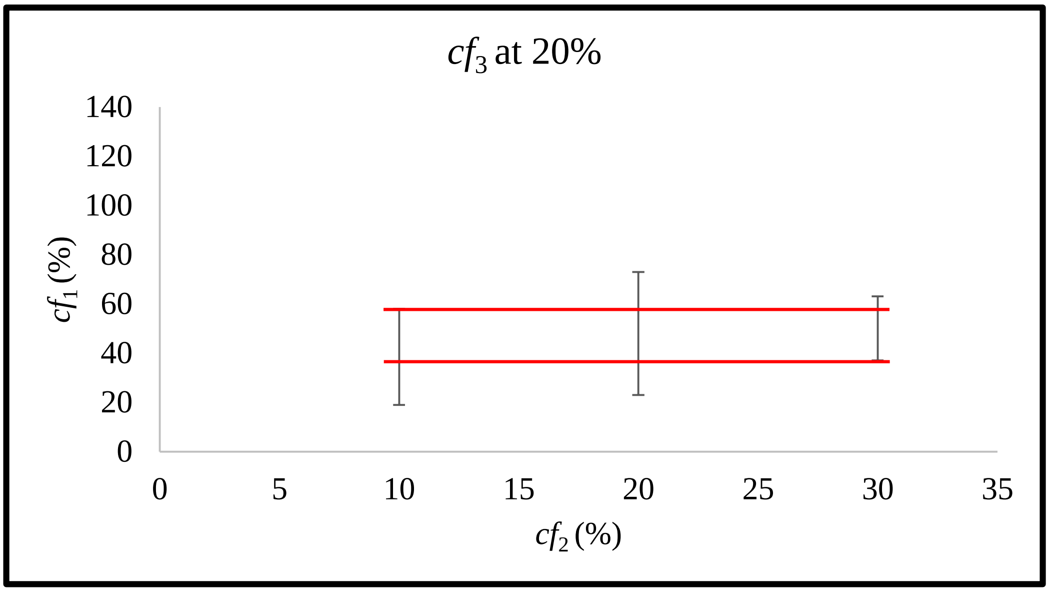

Figure 9.7: Range of cf_1 based on cf_2 with respect to cf_3 = 20%

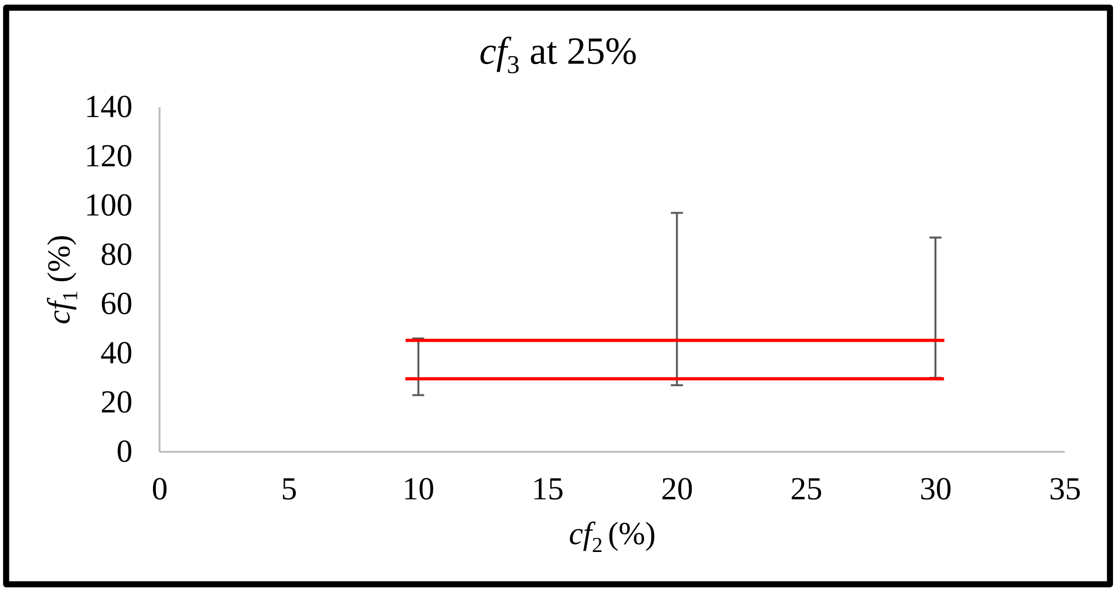

Figure 9.8: Range of cf_1 based on cf_2 with respect to cf_3 = 25%

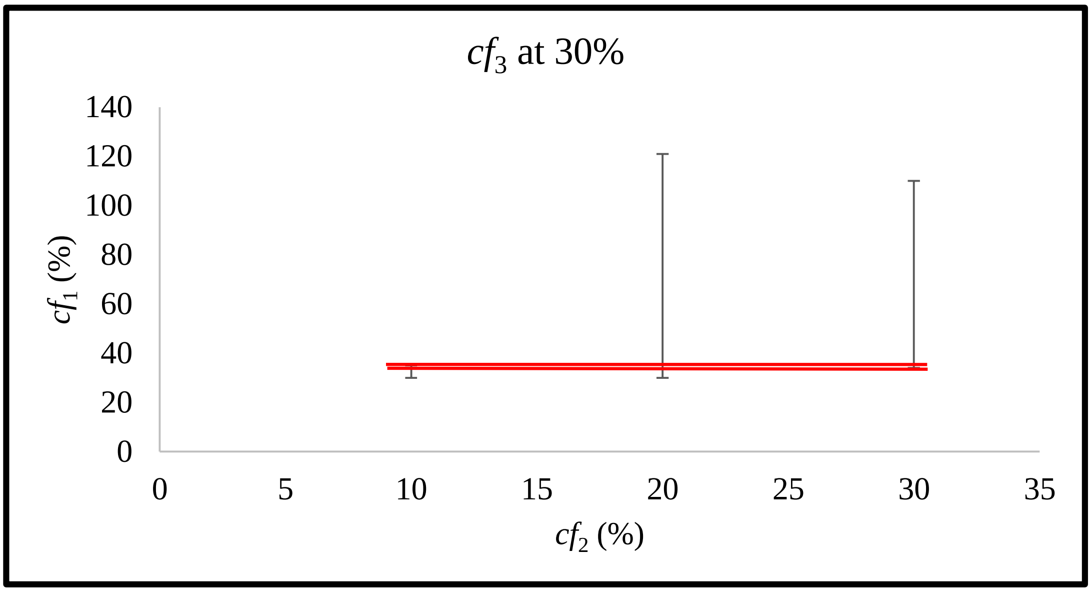

Figure 9.9: Range of cf_1 based on cf_2 with respect to cf_3 = 30%

9.6 Results Analysis

The optimisation results for the case study are summarised in Tables 9.8 – 9.11. As mentioned earlier, CS_1, CS_2 and CS_3 in Table 9.6 represent individual gross profits of the BES, PBB and POM respectively when no coalition is formed. In the case where a coalition is formed among all three facilities, the presented cost savings allocation approach is utilised to determine their deserving individual savings respectively. As shown in Table 9.9, the savings allocated to BES, PBB and POM are US$ 2,100,000, US$ 800,000 and US$ 2,600,000, respectively. Based on these allocations, Table 9.10 indicates that the BES, PBB and POM savings increased by US$ 1,700,000, US$ 600,000 and US$ 1,700,000, respectively. Such increase suggests that cost savings allocated to each plant within the coalition is significantly higher compared to when there is no coalition. This means that these participating plants can be an economically attractive when operated under coalition in an EIP.

Table 9.10: Savings Comparison of PEIP

	Savings without Coalition (US$/yr)	Savings with Coalition (US$/yr)	Increase/Decrease (+/- US$/yr)
BES	400,000	2,100,000	+ 1,700,000
PBB	200,000	800,000	+ 600,000
POM	900,000	2,600,000	+ 1,700,000
Total	**1,500,000**	**5,500,000**	**+ 4,000,000**

Table 9.11: Distribution of Available Palm-based Biomass in PEIP

Palm-based Biomass	Available from POM (kg/h)	Utilised by BES (kg/h)	Utilised by PBB (kg/h)
EFB	12375.00	12375.00	0.00
PMF	6875.00	6875.00	0.00
PKS	3437.50	619.80	2817.70
POME	40700.00	40700.00	0.00

Apart from that, Table 9.11 shows the distribution of the available palm-based biomass within the PEIP. As shown, all of the EFB, PMF and POME are utilised by the BES in order to meet the energy demands of the POM and the PBB.

Specifically, the EFB and PMF biomasses are sent to the water tube boiler in the BES to produce steam and generate power via steam turbines (Figure 9.12). Besides EFB and PMF, POME is processed in an anaerobic digester to yield biogas which is then purified and sent to a gas turbine to generating power. The resulting waste heat from the gas turbine is then recovered via a heat recovery steam generator (HRSG) to produce additional amount of steam (Figure 9.12). Meanwhile, 82% of the PKS biomass is distributed to the PBB to produce methanol fuel while the remaining 18% is sent to the BES for generating steam and power (Table 9.11).

On the other hand, the stability analysis determined the stability threshold of the PEIP coalition. As shown, the PEIP coalition will be stable provided that BES, PBB and POM symbiosis cost fall within 37 to 46%, 10 to 30% and 20 to 25% of their raw material costs, respectively.

9.7 Summary

In this work, an optimisation-based negotiation framework towards fair allocation of total cost savings of a coalition within an eco-industrial park has been demonstrated. The proposed framework integrates the cooperative game model and stability analysis developed by Maali (2009) and the stability criterion proposed by Wang et al. (2013), respectively. It thus considers rational allocation of benefits in the system, while also accounting for the equitable cost-benefit ratios within the coalition to deviations from assumptions pertaining to the costs associated with investments and operations. The framework can used as a negotiation tool for companies to analyse and engage future coalitions, as it can provide a rational basis for an initial profit-sharing EIP scheme. To demonstrate the proposed framework, a palm oil eco-industrial park (PEIP) case study consisting of a biomass tri-generation system (BES), palm-based biorefinery (PBB) and palm oil mill (POM) is analysed.

CHAPTER 10

CONCLUSIONS, CONTRIBUTIONS AND FUTURE WORKS

10.1 Conclusions and Contributions

In this thesis, Chapter 1 introduced the background of the problem faced in the development and design of biomass tri-generation systems. The background serves as the foundation for the theoretical development described in the remaining chapters. Furthermore, the aim and objectives of this research work are identified and presented in Chapter 1. In Chapter 2, an extensive review of Process System Engineering (PSE) approaches developed for the synthesis of energy systems is presented. Following this, the research gaps were highlighted at the end of Chapter 2. Based on the highlighted research gaps, Chapter 3 proposed several research scopes along with a research methodology. Meanwhile, Chapters 4 – 9 provided a detailed description of the contributions from this thesis. The following pointers summarise the key contributions of this thesis;

i. A systematic approach to synthesise and design of a biomass-based energy system (BES) based on seasonal variations in biomass supply and energy demand. In the developed approach, multi-period optimisation was used to simultaneously perform technology and design capacity selection while considering several biomass supply and energy demand scenarios in order to synthesise a BES.

ii. A systematic approach to synthesise a grassroots BES design considering reliability of equipment from a redundancy allocation standpoint. The presented approach addresses complex decisions such as whether to install additional large capacity equipment units, or multiple smaller capacity units, based on their unique reliabilities, capital and operating costs. The approach also determines equipment design capacities along with the total number of operating (and stand-by) equipment for various operating scenarios. This provides a computationally efficient design tool for designers to consult and make informed decisions with respect to reliability issues of a BES.

iii. A systematic approach to synthesise a BES robust towards its operating strategy. This approach simultaneously performs selection of technology, the sizing of equipment and redundancy allocation to cope with equipment failure within the system based on operational strategies considered. This approach offers a tool for designers to consider operating strategies as part of the design decision making procedure.

iv. A systematic framework to analyse the performance of proposed BES designs during failure. This framework provides a systematic procedure to evaluate proposed BES designs under disruption scenarios and analyse their true feasible operating range. Knowledge of the feasible operating range enables designers to determine if a proposed BES design is capable of meeting its intended operations during failure. To illustrate the developed framework, the validation of a palm BES design from Chapter 5 is demonstrated.

v. A systematic framework to debottleneck and retrofit existing BES designs in the case where future energy demand expansion plans are required. The framework provides a decision making tool to re-evaluate an existing BES under disruption scenarios and determine its real-time feasible operating range. Following this, the framework provides designers an informed environment to undertake debottlenecking and retrofit procedures for an existing BES to deliver future energy demands.

vi. An optimisation-based negotiation framework for energy systems in an eco-industrial park (EIP). This framework combines the principles of rational allocation of benefits (based on contributions) with the consideration of stability and robustness of EIP coalitions to changes in cost assumptions. The developed negotiation framework can used as a negotiation tool for companies or policy makers when engaging in future cooperative partnerships, as it provides a rational basis for an initial cost-sharing EIP scheme. It also provides governmental agencies an innovative approach to convince stakeholders to invest in biomass energy and introduce it into the energy marketplace.

10.2 Future Works

As concluded in Section 10.1, this thesis presented systematic approaches that integrate synthesis, design and operation optimisation for a BES. Future research can be conducted to enhance the approaches developed. Several key areas are identified as opportunities for future exploration. These potential future works are summarised in the following;

- **Extension of Multi-Period Optimisation to Two-Stage Stochastic Programming**

The multi-period optimisation approach in Chapter 4 can be extended to two-stage stochastic programming with recourse. In two-stage stochastic programming, violation of the constraints is allowed, but penalised through penalty terms in the objective function. This penalty also known as a recourse variable, leads to additional costs for each scenario. This would mean that every possible parameter realisation in each scenario has an associated recourse action. This approach is suitable for cases where the BES is expected to experience several forms of uncertainties simultaneously during its operation period. However, caution must be given to the model size as stochastic models may become computationally expensive to solve when high number of scenarios are considered. Hence, a trade-off between model size and robustness must also be given priority.

- **Integration of Criticality Analysis with Redundancy Allocation**

In the case where designers are constrained by tight capital budgets, redundancy allocation for the entire BES would not be much favourable. An appropriate resolution for this issue would be to apply the criticality analysis approach presented by Benjamin et al. (2014). The criticality analysis identifies the most crucial components of the BES. By identifying these crucial components, designers can make informed decisions on whether to allocate equipment redundancy based on their restricted budget. Therefore, this combines the criticality analysis approach with the redundancy allocation approach described in Chapter 5 of this thesis.

- **Consideration of Equipment Versatility as part of Redundancy Allocation**

Chapter 5 also provides an opportunity to further explore equipment redundancy allocation. For instance, during the failure of a water-tube boiler, a heat recovery steam generator (HRSG) could be fired up with fuel to provide the required steam to satisfy specified energy demands. Analytical Hierarchical Process (AHP) can be used to rate/rank fuel flexibility of equipment relative to others and subsequently update equipment reliability data accordingly. On the other hand, certain equipment versatile in terms of their source fuel as well. These are other areas of redundancy which can be factored in to formulate a more comprehensive tool to design a reliable BES configuration.

- **Incorporating Disruption Resilience/Response Analysis into Design Validation**

The design validation framework in Chapter 7 can be extended to analyse the disruption resilience or ability of the BES to withstand capacity disruptions and to model the recovery behaviour of disrupted component plants (Michael Francis D Benjamin et al., 2015). Such extensions would enable designers to understand the resilience of the BES against an array of disruption scenarios (i.e., single or multiple disruptions). The proposed extension determines the effects of component interdependencies and type of disruption (i.e., high or low consequence scenario) in the recovery. Risk based insights from this work can be used for planning and developing a more disruption-resilient BES.

- **Performing Life Cycle Assessment of the Biomass-based energy system under Uncertainty**

Another interesting area to explore is the life cycle assessment of the BES under uncertainty. Monte Carlo simulations can be used to actively incorporate input uncertainty to the outcomes (i.e., potential environmental impacts) and provide a way for interpretation of the impact of uncertainties on the outcomes and its quantification. This will also allow designers to rank alternatives according to their quantified environmental performance obtained after being subjected to multi-criteria decision making procedure and probabilistic interpretation.

- **Analysing Rigorous Performances of Unit Operations in the Biomass-based Energy System**

The use of simplified models for processing units for solving a large sized superstructure-based optimisation framework is rather inevitable for process synthesis. This can be further improved to consider more rigorous performances of unit operations by interacting the framework with process simulators such as Aspen HYSYS.

- **Incorporating Considerations of Reliability along with Availability and Maintainability Aspects in Design Decision Making**

This thesis focuses on considering reliability of equipment as part of the design decision making process. According to the Handbook of Reliability, Availability, Maintainability and Safety in Engineering Design, availability is a function of reliability and maintainability. In this respect, future work can be directed towards developing a systematic approach to consider reliability along with availability and maintainability aspects in design decision making.

- **Consideration of Multiple Fuels/Feedstocks for Energy System**

The approaches presented in this thesis are generic in nature. In this respect, future work can also be directed towards analysing the possibility of using multiple sources of fuel aside from biomass.

REFERENCES

Abdullah, N., Sulaiman, F., 2013. The Oil Palm Wastes in Malaysia, in: Biomass Now - Sustainable Growth and Use. InTech.

Aguilar, O., Kim, J.K., Perry, S., Smith, R., 2008. Availability and Reliability Considerations in the Design and Optimisation of Flexible Utility Systems. Chemical Engineering Science 63, 3569–3584.

Aguilar, O., Perry, S.J., Kim, J.-K., Smith, R., 2007a. Design and Optimization of Flexible Utility Systems Subject to Variable Conditions Part 1: Modelling Framework. Chemical Engineering Research and Design 85, 1136–1148.

Aguilar, O., Perry, S.J., Kim, J.-K., Smith, R., 2007b. Design and Optimization of Flexible Utility Systems Subject to Variable Conditions Part 2: Methodology and Applications. Chemical Engineering Research and Design 85, 1149–1168.

Ahmad, S., Polley, G.T., 1990. Debottlenecking of Heat Exchanger Networks. Heat Recovery Systems and CHP 10, 369–385.

Air-Conditioning Heating & Refrigeration Institute, 2000. Standard for Absorption Water Chilling and Water Heating Packages.

Alshekhli, O., Foo, D.C.Y., Hii, C.L., Law, C.L., 2010. Process Simulation and Debottlenecking for an Industrial Cocoa Manufacturing Process. Food and Bioproducts Processing 89, 528–536.

Al-Sulaiman, F., Hamdullahpur, F., Dincer, I., 2011. Trigeneration: a comprehensive review based on prime movers. International Journal of Energy Research 233–258.

American Soybean Association, 2014. International: World Vegetable Oil Consumption 2012 [WWW Document]. URL http://soystats.com/international-world-vegetable-oil-consumption/ (accessed 5.8.14).

Arcuri, P., Beraldi, P., Florio, G., Fragiacomo, P., 2015. Optimal Design of a Small Size Trigeneration Plant in Civil Users: A MINLP (Mixed Integer Non Linear Programming Model). Energy 80, 628–641.

Atkins, M., Walmsley, M., Morrison, A., Neale, J., 2011. Process Integration in Pulp and Paper Mills for Energy and Water Reduction - a Review, in: 65th Appita Annual Conference and Exhibition: Rotorua New Zealand 10-13 April 2011. Appita Inc., Carlton, Vic., pp. 299–306.

Aviso, K.B., 2014. Design of Robust Water Exchange Networks for Eco-industrial Symbiosis. Process Safety and Environmental Protection 92, 160–170.

Aviso, K.B., Tan, R.R., Culaba, A.B., 2010a. Designing Eco-industrial Water Exchange Networks using Fuzzy Mathematical Programming. Clean Technologies and Environmental Policy 12, 353–363.

Aviso, K.B., Tan, R.R., Culaba, A.B., Jr., J.B.C., 2010b. Bi-level Fuzzy Optimization Approach for Water Exchange in Eco-industrial Parks. Process Safety and Environmental Protection 88, 31–40.

Baldea, M., 2015. From Process Integration to Process Intensification. Computers and Chemical Engineering 81, 104–114.

Baños, R., Manzano-Agugliaro, F., Montoya, F.G., Gil, C., Alcayde, A., Gómez, J.,

2011. Optimization Methods Applied to Renewable and Sustainable Energy: A Review. Renewable and Sustainable Energy Reviews 15, 1753–1766.

Barnicki, S.D., Siirola, J.J., 2004. Process Synthesis Prospective. Computers & Chemical Engineering 28, 441–446.

Bauer, F., Hulteberg, C., Persson, T., Tamm, D., 2013. Biogas Upgrading – Review of Commercial Technologies.

Beith, R., 2011. Small and Micro Combined Heat and Power (CHP) Systems: Advanced Design, Peferomance, Materials and Applications [WWW Document]. Woodhead Publishing Limited.

Bellman, R.E., Zadeh, L.A., 1970. Decision-Making in a Fuzzy Environment. Management Science 17, B–141–B–164.

Bengtson, H., 2011. Principles of the Vapor Compression Refrigeration System [WWW Document]. URL http://www.brighthubengineering.com/hvac/35435-principles-of-the-vapor-compression-refrigeration-system/ (accessed 7.2.14).

Benjamin, M.F.D., Tan, R.R., Razon, L.F., 2015. Probabilistic Multi-Disruption Risk Analysis in Bioenergy Parks via Physical Input – Output Modeling and Analytic Hierarchy Process. Sustainable Production and Consumption 1, 22–33.

Benjamin, M.F.D., Tan, R.R., Razon, L.F., 2014. A Methodology for Criticality Analysis in Integrated Energy Systems. Clean Technologies and Environmental Policy 17, 935–946.

Benjamin, M.F.D., Ubando, A.T., Razon, L.F., Tan, R.R., 2015. Analyzing the Disruption Resilience of Bioenergy Parks using Dynamic Inoperability Input-Output Modeling. Environment Systems and Decisions 35, 351–362.

Ben-Tal, A., Nemirovski, A., 1998. Robust Convex Optimization. Mathematics of Operations Research 23, 769–805.

Bertsimas, D., Brown, D.B., Caramanis, C., 2010. Theory and Applications of Robust Optimization. Operations Research 50.

Biegler, L.T., Grossmann, I.E., Westerberg, A.W., 1997. Systematic Methods of Chemical Process Design. Prentice Hall, New Jersey.

Bischi, A., Taccari, L., Martelli, E., Amaldi, E., Manzolini, G., Silva, P., Campanari, S., Macchi, E., 2014. A Detailed MILP Optimization Model for Combined Cooling , Heat and Power System Operation Planning. Energy 74, 12–26.

BISYPLAN, 2012. BISYPLAN Web-based handbook [WWW Document]. URL http://bisyplan.bioenarea.eu/html-files-en/04-01.html (accessed 9.17.14).

Boden, T.A., Marland, G., Andres, R.J., 2012. Global, Regional, and National Fossil-Fuel CO2 Emissions [WWW Document]. URL http://cdiac.ornl.gov/trends/emis/overview.html (accessed 5.8.14).

Boix, M., Montastruc, L., Azzaro-Pantel, C., Domenech, S., 2015. Optimization Methods Applied to the Design of Eco-industrial Parks: A Literature Review. Journal of Cleaner Production 87, 303–317.

Boyle, G., 2011. Energy Use in Agriculture.

Bridgwater, A. V, 2003. Renewable Fuels and Chemicals by Thermal Processing of Biomass. Chemical Engineering Journal 91, 87–102.

British Petroluem, 2013. BP Statistical Review of World Energy.

Buoro, D., Casisi, M., De Nardi, A., Pinamonti, P., Reini, M., 2013. Multicriteria Optimization of a Distributed Energy Supply System for an Industrial Area. Energy 58, 128–137.

Buoro, D., Casisi, M., Pinamonti, P., Reini, M., 2012. Optimal Synthesis and Operation of Advanced Energy Supply Systems for Standard and Domotic Home. Energy Conversion and Management 60, 96–105.

Buoro, D., Casisi, M., Pinamonti, P., Reini, M., 2011. Optimization of Distributed Trigeneration Systems Integrated with Heating and Cooling Micro-grids. Distributed Generation & Alternative Energy Journal 26, 7–34.

Buoro, D., Casisi, M., Pinamonti, P., Reini, M., 2010. Optimal Lay-Out and Operation of District Heating and Cooling Distributed Trigeneration Systems, in: ASME Turbo Expo 2010: Power for Land, Sea, and Air. ASME, pp. 157–166.

Cai, Y.P., Huang, G.H., Yang, Z.F., Lin, Q.G., Tan, Q., 2009. Community Scale Renewable Energy Systems Planning under Uncertainty—An Interval Chance-Constrained Programming Approach. Renewable and Sustainable Energy Reviews 13, 721–735.

Carpaneto, E., Chicco, G., Mancarella, P., Russo, A., 2011a. Cogeneration Planning under Uncertainty Part I: Multiple Time Frame Approach. Applied Energy 88, 1059–1067.

Carpaneto, E., Chicco, G., Mancarella, P., Russo, A., 2011b. Cogeneration Planning under Uncertainty Part II: Decision Theory-based Assessment of Planning Alternatives. Applied Energy 88, 1075–1083.

Carvalho, M., Lozano, M. a, Ramos, J., Serra, L.M., 2013. Synthesis of Trigeneration Systems: Sensitivity Analyses and Resilience. TheScientificWorldJournal 2013, 604852.

Carvalho, M., Lozano, M. a., Serra, L.M., 2012. Multicriteria Synthesis of Trigeneration Systems Considering Economic and Environmental Aspects. Applied Energy 91, 245–254.

Carvalho, M., Serra, L.M., Lozano, M.A., 2011. Optimal Synthesis of Trigeneration Systems Subject to Environmental Constraints. Energy 36, 3779–3790.

Cecelja, F., Kokossis, A., Du, D., 2011. Integration of Ontology and Knowledge-based Optimization in Process Synthesis Applications, in: Computer Aided Chemical Engineering. pp. 427–431.

Černý, V., 1985. Thermodynamical Approach to the Traveling Salesman Problem: An Efficient Simulation Algorithm. Journal of Optimization Theory and Applications 45, 41–51.

Chae, S.H., Kim, S.H., Yoon, S.G., Park, S., 2010. Optimization of a Waste Heat Utilization Network in an Eco-industrial Park. Applied Energy 87, 1978–1988.

Chang, C.-T., Hwang, J.-R., 1996. A Multiobjective Programming Approach to Waste Minimization in the Utility Systems of Chemical Processes. Chemical Engineering Science 51, 3951–3965.

Chankong, V., Haimes, Y.Y., 1983. Multiobjective Decision Making: Theory and Methodology. North Holland.

Charnes, A., Cooper, W.W., 1963. Deterministic Equivalents for Optimizing and

Satisficing under Chance Constraints. Operations Research 11, 18–39.

Charnes, A., Cooper, W.W., 1962. Chance Constraints and Normal Deviates. Journal of American Statistical Association 57, 134–148.

Charnes, A., Cooper, W.W., 1959. Chance-Constrained Programming. Management Science 6, 73–79.

Chartered Institution of Building Services Engineers, 2012. Absorption Cooling.

Chen, C.L., Lin, C.Y., 2012. Retrofit of Steam Power Plants in Eco-industrial Parks. Chemical Engineering Transactions 29, 145–150.

Chew, I.M.L., Foo, D.C.Y., 2009. Automated Targeting for Inter-plant Water Integration. Chemical Engineering Journal 153, 23–36.

Chew, I.M.L., Foo, D.C.Y., Ng, D.K.S., Tan, R.R., 2010a. Flowrate Targeting Algorithm for Interplant Resource Conservation Network. Part 1: Unassisted Integration Scheme. Industrial & Engineering Chemistry Research 49, 6439–6455.

Chew, I.M.L., Foo, D.C.Y., Tan, R.R., 2010b. Flowrate Targeting Algorithm for Interplant Resource Conservation Network . Part 2 : Assisted Integration Scheme. Industrial & Engineering Chemistry Research 49, 6456–6468.

Chew, I.M.L., Tan, R.R., Foo, D.C.Y., Chiu, A.S.F., 2009. Game Theory Approach to the Analysis of Inter-plant Water Integration in an Eco-industrial Park. Journal of Cleaner Production 17, 1611–1619.

Chicco, G., Mancarella, P., 2009. Distributed Multi-Generation: A Comprehensive View. Renewable and Sustainable Energy Reviews 13, 535–551.

Chicco, G., Mancarella, P., 2008. Assessment of the Greenhouse Gas Emissions from Cogeneration and Trigeneration Systems. Part I: Models and Indicators. Energy 33, 410–417.

Chin, M.J., Poh, P.E., Tey, B.T., Chan, E.S., Chin, K.L., 2013. Biogas from Palm Oil Mill Effluent (POME): Opportunities and Challenges from Malaysia's Perspective. Renewable and Sustainable Energy Reviews 26, 717–726.

Cho, H., Smith, A.D., Mago, P., 2014. Combined Cooling, Heating and Power: A Review of Performance Improvement and Optimization. Applied Energy 136, 168–185.

Climate Works Australia, 2011. Unlocking Barriers to Cogeneration. Melbourne, Australia.

Coit, D.W., Liu, J., 2000. System Reliability Optimization with k-out-of-m subsystems. International Journal of Reliability, Quality and Safety Engineering 7, 129–142.

Combined Heat and Power Association, 2014. What is CHP? [WWW Document]. URL http://www.chpa.co.uk/what-is-chp_15.html (accessed 5.10.14).

Dantzig, G.B., 1955. Linear Programming under Uncertainty. Management Science 1, 197 – 206.

Deb, K., 2001. Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley & Sons, Chichester, United Kingdom.

Del Nogal, F., Kim, J.-K., Perry, S., Smith, R., 2005. Systematic Driver and Power Plant selection for Power-demanding Industrial Processes, in: AIChE Spring

Meeting. Atlanta.

Dhole, V.R., Linnhoff, B., 1993. Total site targets for fuel, co-generation, emissions, and cooling. Computers & Chemical Engineering 17, S101–S109.

Diaz, S., Serrani, A., Beistegui, R.D., Brignole, E.A., 1995. A MINLP strategy for the debottlenecking problem in an ethane extraction plant. Computers & Chemical Engineering 19, 175–180.

Dimian, A.C., Bildea, C.S., Kiss, A.A., 2014. Integrated Design and Simulation of Chemical Processes, 2nd ed. Amsterdam.

Dimopoulos, G.G., Kougioufas, A. V., Frangopoulos, C. a., 2008. Synthesis, design and operation optimization of a marine energy system. Energy 33, 180–188.

Douglas, J.M., 1988. Conceptual Design of Chemical Processes. New York.

Dua, V., Pistikopoulos, E.N., 1999. Algorithms for the Solution of Multiparametric Mixed-Integer Nonlinear Optimization Problems. Industrial & Engineering Chemistry Research 38, 3976–3987.

Ebeling, C.E., 1997. An Introduction to Reliability and Maintainability Engineering. McGraw Hill.

Edgar, T.F., Himmelblau, D.M., Lasdon, L.S., 2001. Optimization of Chemical Processes. McGraw-Hill.

EIA, 2014. International Energy Data and Analysis - Malaysia.

Eiben, A.E., Smith, J.E., 2003. Introduction to Evolutionary Computing. Springer Science & Business Media.

El-Halwagi, M.M., 2007. Process Integration. Academic Press.

Environmental Leader, 2013. Conventional Energy, Environmental Management & Energy News · Environmental Leader [WWW Document]. URL http://www.environmentalleader.com/category/conventional-energy/ (accessed 5.8.14).

Fang, F., Wang, Q.H., Shi, Y., Member, S., 2012. A Novel Optimal Operational Strategy for the CCHP System Based on Two Operating Modes. IEEE Transactions on Power Systems 27, 1032–1041.

Floudas, C.A., 1995. Nonlinear and Mixed-Integer Optimization, Handbook of Applied Optimization.

Frangopoulos, C.A., 2003. Methods of Energy Systems Optimization.

Frangopoulos, C.A., Dimopoulos, G.G., 2004. Effect of Reliability Considerations on the Optimal Synthesis, Design and Operation of a Cogeneration System. Energy 29, 309–329.

Frangopoulos, C.A., Von Spakovsky, M.R., Sciubba, E., 2002. A Brief Review of Methods for the Design and Synthesis Optimization of Energy Systems. International Journal of Applied Thermodynamics 5, 151–160.

Frosch, R.A., Gallopoulos, N.E., 1989. Strategies for Manufacturing, in: Scientific American. pp. 1–7.

Gau, C.-Y., Schrage, L.E., 2004. Implementation and Testing of a Branch-and-Bound Based Method for Deterministic Global Optimization: Operations Research Applications, in: Floudas, C.A., Pardalos, P. (Eds.), Frontiers in

Global Optimization, Nonconvex Optimization and Its Applications. Springer US, Boston, MA.

Ghadimi, P., Kara, S., Kornfeld, B., 2014. The Optimal Selection of On-site CHP Systems through Integrated Sizing and Operational Strategy. Applied Energy 126, 38–46.

Godoy, E., Benz, S.J., Scenna, N.J., 2015. An Optimization Model for Evaluating the Economic impact of Availability and Maintenance Notions during the Synthesis and Design of a Power Plant. Computers & Chemical Engineering 75, 135–154.

Goel, H.D., Grievink, J., Herder, P.M., Weijnen, M.P.C., 2002. Integrating Reliability Optimization into Chemical Process Synthesis. Reliability Engineering & System Safety 78, 247–258.

Goel, H.D., Grievink, J., Weijnen, M.P.C., 2003. Integrated Optimal Reliable Design, Rroduction, and Maintenance Planning for Multipurpose Process Plants. Computers & Chemical Engineering 27, 1543–1555.

Gonela, V., Zhang, J., 2014. Design of the Optimal Industrial Symbiosis System to Improve Bioethanol Production. Journal of Cleaner Production 64, 513–534.

Goodell, M., 2006. Trigeneration [WWW Document]. URL http://cogeneration.net/Trigeneration.htm (accessed 5.5.14).

Greenwise, 2011. Biofuels 101: Biofuels from Generation to Generation [WWW Document]. URL http://livinggreenandsavingenergy.com/biofuels-101-biofuels-from-generation-to-generation.html

Grossmann, E., Westerberg, A.W., 2000. Research Challenges in Process Systems Engineering. AIChE Journal 46, 1700–1703.

Grossmann, I.E., 2002. Review of Nonlinear Mixed-Integer and Disjunctive Programming Techniques. Methods 3, 227–252.

Grossmann, I.E., Daichendt, M.M., 1996. New Trends in Optimization-based Approaches to Process Synthesis. Computers & Chemical Engineering.

Grossmann, I.E., Guillén-Gosálbez, G., 2010a. Scope for the Application of Mathematical Programming Techniques in the Synthesis and Planning of Sustainable Processes. Computers & Chemical Engineering 34, 1365–1376.

Grossmann, I.E., Guillén-Gosálbez, G., 2010b. Scope for the Application of Mathematical Programming Techniques in the Synthesis and Planning of Sustainable Processes, in: Computers & Chemical Engineering. pp. 1365–1376.

Grossmann, I.E., Morari, M., 1984. Operability, Resiliency and Flexibility – Process Design Objectives for a Changing World, in: AW, W., HH, C. (Eds.), Proceedings of 2nd International Conference on Foundations of Computer-Aided Process Design. p. 931.

Grossmann, I.E., Morari, M., 1983. Operability, Resiliency, and Flexibility: process design objectives for a changing world.

Grossmann, I.E., Sargent, R.W.H., 1978. Optimum Design of Chemical Plants with Uncertain Parameters. AIChE Journal 24, 1021–1028.

Haimes, Y., Jiang, P., 2001. Leontief-Based Model of Risk in Complex Interconnected Infrastructures. Journal of Infrastructure Systems 7, 1–12.

Haimes, Y.Y., Lasdon, L.S., Wimser, D.A., 1971. On a Bicriterion Formulation of the Problems of Integrated System Identification and System Optimization 47, 296–297.

Hajela, P., Lin, C.-Y., 1992. Genetic Search Strategies in Multicriterion Optimal Design. Structural Optimization 4, 99–107.

Halemane, K.P., Grossmann, E., 1983. Optimal Process Design under Uncertainty. AIChE Journal 29, 425–433.

Harsh, M.G., Saderne, P., Biegler, L.T., 1989. A Mixed Integer Flowsheet Optimization Strategy for Process Retrofits—The Debottlenecking Problem. Computers & Chemical Engineering 13, 947–957.

Hastings, D., McManus, H., 2004. A Framework for Understanding Uncertainty and its Mitigation and Exploitation in Complex Systems, in: Engineering Systems Symposium. pp. 1–19.

Haywood, R.W., 1980. Analysis of Engineering Cycles. Pergamon Press.

Hendry, J.E., Rudd, D.F., Seader, J.D., 1973. Synthesis in the Design of Chemical Processes. AIChE Journal 19, 1–15.

Herder, P.M., Weijnen, M.P.C., 2000. A Concurrent Engineering Approach to Chemical Process Design. International Journal of Production Economics, Int. J. Prod. Econ. (Netherlands) 64, 311–318.

Hiete, M., Ludwig, J., Schultmann, F., 2012. Intercompany Energy Integration. Journal of Industrial Ecology 16, 689–698.

Hill, J., Nelson, E., Tilman, D., Polasky, S., Tiffany, D., 2006. Environmental, Economic, and Energetic Costs and Benefits of Biodiesel and Ethanol Biofuels, in: Proceedings of the National Academy of Sciences. pp. 11206–11210.

Hiremath, R.B., Shikha, S., Ravindranath, N.H., 2007. Decentralized Energy Planning; Modeling and Application—A Review. Renewable and Sustainable Energy Reviews 11, 729–752.

Hobbs, B.F., 1995. Optimization Methods for Electric Utility Resource Planning. European Journal of Operational Research 83, 1–20.

Holling, C., 1996. Engineering Within Ecological Constraints. National Academies Press, Washington D.C.

Hondeman, H., 2000. Electrical compression cooling versus absorption cooling - a comparison. IEA Heat Pump Centre Newsletter 18.

Horst, R., Tuy, H., 1996. Global Optimization: Deterministic Approaches. Springer Science & Business Media.

Hui, C.-W., Natori, Y., 1996. An Industrial Application using Mixed-Integer Programming Technique: A Multi-Period Utility System Model. Computers & Chemical Engineering 20, S1577–S1582.

Husain, Z., Zainac, Z., Abdullah, Z., 2002. Briquetting of Palm Fibre and Shell from the Processing of Palm Nuts to Palm Oil. Biomass and Bioenergy 22, 505–509.

Ishibuchi, H., Murata, T., 1998. A Multi-Objective Genetic Local Search Algorithm and Its Application to Flowshop Scheduling. IEEE Transactions on Systems, Man, Cybernetics—Part C: Applications and Review 28, 392–403.

Iyer, R.R., Grossmann, I.E., 1998. Synthesis and Operational Planning of Utility Systems for Multiperiod Operation. Computers & Chemical Engineering 22, 979–993.

Jackson, T., Clift, R., 1998. Where's the Profit in Industrial Ecology? Journal of Industrial Ecology 2, 3–5.

Jalalzadeh-Azar, A.., 2004. A Comparison of Electrical- and Thermal-Load-Following CHP Systems, in: 2004 Annual Meeting of the American Society of Heating, Refrigerating and Air-Conditioning Engineers. Nashville, TX; United States, pp. 85–94.

Jing, Y.-Y., Bai, H., Wang, J.-J., 2012. Multi-objective Optimization Design and Operation Strategy Analysis of BCHP System based on Life Cycle Assessment. Energy 37, 405–416.

Joseph, K., 2015. Fuel for a Sustainable Future. Engage 1–4.

Jradi, M., Riffat, S., 2014. Tri-generation Systems: Energy Policies, Prime Movers, Cooling Technologies, Configurations and Operation Strategies. Renewable and Sustainable Energy Reviews 32, 396–415.

Kasivisvanathan, H., Barilea, I.D.U., Ng, D.K.S., Tan, R.R., 2013. Optimal Operational Adjustment in Multi-functional Energy Systems in Response to Process Inoperability. Applied Energy 102, 492–500.

Kasivisvanathan, H., Ng, R.T.L., Tay, D.H.S., Ng, D.K.S., 2012. Fuzzy Optimisation for Retrofitting a Palm Oil Mill into a Sustainable Palm Oil-based Integrated Biorefinery. Chemical Engineering Journal 200–202, 694–709.

Kasivisvanathan, H., Tan, R.R., Ng, D.K.S., Abdul Aziz, M.K., Foo, D.C.Y., 2014a. Heuristic Framework for the Debottlenecking of a Palm Oil-based Integrated Biorefinery. Chemical Engineering Research and Design 92, 2071–2082.

Kasivisvanathan, H., Ubando, A.T., Ng, D.K.S., Tan, R.R., 2014b. Robust Optimization for Process Synthesis and Design of Multifunctional Energy Systems with Uncertainties. Industrial & Engineering Chemistry Research 53, 3196–3209.

Kavvadias, K.C., Tosios, A.P., Maroulis, Z.B., 2010. Design of a Combined Heating, Cooling and Power System: Sizing, Operation Strategy Selection and Parametric Analysis. Energy Conversion and Management 51, 833–845.

Kelly-Yong, T.L., Lee, K.T., Mohamed, A.R., Bhatia, S., 2007. Potential of Hydrogen from Oil Palm Biomass as a Source of Renewable Energy Worldwide. Energy Policy 35, 5692–5701.

Kemp, I.C., 2007. Pinch Analysis and Process Integration: A User Guide on Process Integration for the Efficient Use of Energy. Butterworth-Heinemann.

Kim, S.H., Yoon, S.G., Chae, S.H., Park, S., 2010. Economic and Environmental Optimization of a Multi-site Utility Network for an Industrial Complex. Journal of Environmental Management 91, 690–705.

Kirkpatrick, S., 1984. Optimization by Simulated Annealing: Quantitative Studies. Journal of Statistical Physics 34, 975–986.

Kopanos, G.M., Pistikopoulos, E.N., 2014. Reactive Scheduling by a Multiparametric Programming Rolling Horizon Framework : A Case of a Network of Combined Heat and Power Units. Industrial & Engineering Chemistry Research 53, 4366–4386.

Korhonen, J., 2001. Co-production of heat and power : an anchor tenant of a regional industrial ecosystem. Journal of Cleaner Production 9, 509–517.

Koulouris, A., Calandranis, J., Petrides, D.P., 2000. Throughput Analysis and Debottlenecking of Integrated Batch Chemical Processes. Computers & Chemical Engineering 24, 1387–1394.

Kronenberg, J., 2007. Ecological Economics and Industrial Ecology: A Case Study of the Integrated Product Policy of the European Union. Routledge, New York.

Kuo, W., Zhu, X., 2012. Importance Measures in Reliability, Risk, and Optimization. John Wiley and Sons Inc.

Land, A.H., Doig, A.G., 1960. An Automatic Method of Solving Discrete Programming Problems. Econometrica 28, 497–520.

Leete, R., 2007. Malaysia Generating Renewable Energy from Palm Oil Wastes. United Nations Development Programme Malaysia.

Leiras, A., Elkamel, A., Hamacher, S., 2010. Strategic Planning of Integrated Multirefinery Networks : A Robust Optimization. Industrial & Engineering Chemistry Research 49, 9970–9977.

Li, C.-Z., Shi, Y.-M., Liu, S., Zheng, Z., Liu, Y., 2010. Uncertain Programming of Building Cooling Heating and Power (BCHP) System based on Monte-Carlo Method. Energy and Buildings 42, 1369–1375.

Li, X., Kraslawski, A., 2004. Conceptual Process Synthesis: Past and Current Trends. Chemical Engineering and Processing: Process Intensification 43, 583–594.

Liew, P.Y., Wan Alwi, S.R., Varbanov, P.S., Manan, Z.A., Klemeš, J.J., 2013. Centralised Utility System Planning for a Total Site Heat Integration network. Computers & Chemical Engineering 57, 104–111.

Lim, S.R., Park, J.M., 2010. Interfactory and Intrafactory Water Network System to Remodel a Conventional Industrial Park to a Green Eco-industrial park, in: Industrial and Engineering Chemistry Research. pp. 1351–1358.

Lin, Z., Zheng, Z., Smith, R., Yin, Q., 2012. Reliability Issues in the Design and Optimization of Process Utility Systems. Theoretical Foundations of Chemical Engineering 46, 747–754.

LINDO Systems Inc., 2011. LINDO User's Guide.

Linnhoff, B., Townsend, D.W., Boland, D., Hewitt, G.F., Thomas, B.E.A., R., G.A., Marsland, R.H., 1982. A User Guide on Process Integration for the Efficient Use of Energy. Institution of Chemical Engineers.

Litzen, D.B., Bravo, J.L., 1999. Uncover Low-cost Debottlenecking Opportunities. CHemical Engineering Progress 95, 25–32.

Liu, M., Shi, Y., Fang, F., 2014a. Combined Cooling, Heating and Power Systems: A Survey. Renewable and Sustainable Energy Reviews 35, 1–22.

Liu, M., Shi, Y., Fang, F., 2014b. Combined Cooling, Heating and Power Systems: A Survey. Renewable and Sustainable Energy Reviews 35, 1–22.

Liu, P., 2009. Modelling and Optimization of Polygeneration Energy Systems.

Liu, P., Georgiadis, M.C., Pistikopoulos, E.N., 2013. An Energy Systems Engineering Approach for the Design and Operation of Microgrids in Residential Applications. Chemical Engineering Research and Design 91, 2054–2069.

Liu, P., Georgiadis, M.C., Pistikopoulos, E.N., 2011. Advances in Energy Systems Engineering. Industrial & Engineering Chemistry Research 50, 4915–4926.

López-Díaz, D.C., Lira-Barragán, L.F., Rubio-Castro, E., Ponce-Ortega, J.M., El-Halwagi, M.M., 2015. Synthesis of Eco-Industrial Parks Interacting with a Surrounding Watershed. ACS Sustainable Chemistry & Engineering 3, 1564–1578.

Lowe, E.A., 2001. Eco-Industrial Park Handbook for Asian Developing Countries. Indigo Development.

Lowe, E.A., Moran, S.R., Holmes, D.B., 1996. Fieldbook for the Development of Eco-Industrial Parks. Indogo Development, Oakland, California.

Lozano, M. a., Carvalho, M., Serra, L.M., 2011. Allocation of Economic Costs in Trigeneration Systems at Variable Load Conditions. Energy and Buildings 43, 2869–2881.

Lozano, M. a., Ramos, J.C., Carvalho, M., Serra, L.M., 2009. Structure Optimization of Energy Supply Systems in Tertiary Sector Buildings. Energy and Buildings 41, 1063–1075.

Lozano, M. a., Ramos, J.C., Serra, L.M., 2010. Cost Optimization of the Design of CHCP (Combined Heat, Cooling and Power) Systems under Legal Constraints. Energy 35, 794–805.

Luo, X., Hu, J., Zhao, J., Zhang, B., Chen, Y., Mo, S., 2014. Multi-objective Optimization for the Design and Synthesis of Utility Systems with Emission Abatement Technology Concerns. Applied Energy 136, 1110–1131.

Luo, X., Zhang, B., Chen, Y., Mo, S., 2013. Operational Planning Optimization of Steam Power Plants considering Equipment Failure in Petrochemical Complex. Applied Energy 112, 1247–1264.

Maali, Y., 2009. A Multiobjective Approach for Solving Cooperative n-person Games. International Journal of Electrical Power & Energy Systems 31, 608–610.

Mago, P.J., Chamra, L.M., 2009. Analysis and Optimization of CCHP Systems based on Energy, Economical, and Environmental Considerations. Energy and Buildings 41, 1099–1106.

Mago, P.J., Hueffed, A.K., 2010. Evaluation of a Turbine Driven CCHP System for Large Office Buildings under Different Operating Strategies. Energy and Buildings 42, 1628–1636.

Mago, P.J.Ã., Fumo, N., Chamra, L.M., 2009. Performance Analysis of CCHP and CHP Systems Operating following the Thermal and Electric Load. International Journal of Energy Research 852–864.

Maheri, A., 2014. A Critical Evaluation of Deterministic Methods in Size Optimisation of Reliable and Cost Effective Standalone hybrid Renewable Energy Systems. Reliability Engineering & System Safety 130, 159–174.

Majutek Perunding, 2014. The Trigeneration Advantage [WWW Document]. URL http://majutekperunding.tripod.com/cogenerationanddistrictcoolingsystemspecialist/id7.html (accessed 5.5.14).

Malaysian Danish Environmental Cooperation Programme, 2005. Barrier Analysis for the Supply Chain of Palm Oil Processing Biomass (Empty Fruit Bunch) as Renewable Fuel.

Malaysian Innovation Agency (AIM), 2013. National Biomass Strategy 2020: New wealth creation for Malaysia's palm oil industry.

Malaysian Palm Oil Board, 2014. Annual and Forecast of Crude Palm Oil 2013 & 2014 [WWW Document]. URL http://bepi.mpob.gov.my/index.php/statistics/production/125-production-2014/657-annual-forecast-production-of-crude-palm-oil-2013-2014.html

Malaysian Palm Oil Council, 2012. Malaysian Palm Oil Industry [WWW Document]. URL http://www.mpoc.org.my/Malaysian_Palm_Oil_Industry.aspx

Malaysian Palm Oil Council, 2006. Palm oil & Palm Kernel Oil Applications [WWW Document]. URL http://www.mpoc.org.my/Palm_Oil_and_Palm_Kernel_Oil_Applications.aspx (accessed 5.8.14).

Marechal, F., Kalitventzeff, B., 2003. Targeting the Integration of Multi-Period Utility Systems for Site Scale Process Integration. Applied Thermal Engineering 23, 1763–1784.

Maréchal, F., Kalitventzeff, B., 1998. Process Integration: Selection of the Optimal Utility System. Computers & Chemical Engineering 22, S149–S156.

Mayer, A.L., 2008. Ecologically-based Approaches to Evaluate the Sustainability of Industrial Systems. International Journal of Sustainable Society 1, 117–133.

Mehleri, E.D., Sarimveis, H., Markatos, N.C., Papageorgiou, L.G., 2013. Optimal Design and Operation of Distributed energy Systems: Application to Greek Residential Sector. Renewable Energy 51, 331–342.

MES, 2016. Technical Safety/HSE Risk Management/Asset Integrity & Operational Assurance [WWW Document]. URL http://www.mes-international.com/safety-engineering.php (accessed 1.6.16).

Misener, R., Gounaris, C.E., Floudas, C.A., 2009. Global Optimization of Gas Lifting Operations: A Comparative Study of Piecewise Linear Formulations. Industrial & Engineering Chemistry Research 48, 6098–6104.

Mitra, S., Sun, L., Grossmann, I.E., 2013. Optimal Scheduling of Industrial Combined Heat and Power Plants under Time-sensitive Electricity Prices. Energy 54, 194–211.

Moorthy, K., 2014. Re-engineering palm oil mills into centres of energy efficiency | Sustainable palm oil [WWW Document]. URL http://betterpalmoildebate.org/features/post.php?s=2014-01-10-re-engineering-palm-oil-mills-into-centres-of-energy-efficiency (accessed 5.9.14).

Moulijn, J.A., Stankiewicz, A., Grievink, J., Andrzej, G., 2008. Process Intensification and Process Systems Engineering: A Friendly Symbiosis. Computers & Chemical Engineering 32, 3–11.

Mulvey, J.M., Vanderbei, R., Zenios, S.A., Vanderbei, R.J., 1995. Robust Optimization of Large-Scale Systems. Operations Research 43, 264–281.

Murphy, W.K., Masters, K.R., 1978. Gross Heat of Combustion of Northern Red Oak (Quercus Rubra) Chemical Components. Wood Science 10, 139–141.

Naik, S.N., Goud, V. V., Rout, P.K., Dalai, A.K., 2010. Production of First and Second Generation Biofuels: A Comprehensive Review. Renewable and Sustainable Energy Reviews 14, 578–597.

Nasrin, A.B., Ma, A.N., Choo, Y.M., Mohamad, S., Rohaya, M.H., Azali, A., Zainal, Z., 2008. Oil Palm Biomass As Potential Substitution Raw Materials For Commercial Biomass Briquettes Production. American Journal of Applied Sciences 5, 179–183.

Natural Resources Defense Council, 2014. Renewable Energy for America: Biogas [WWW Document]. URL http://www.nrdc.org/energy/renewables/biogas.asp (accessed 5.14.14).

Ng, C., 2013. Malaysia's Palm Oil Industry: Developing Green Technologies While Ensuring Sustainability 6–8.

Ng, R.T.L., Ng, D.K.S., 2013. Systematic Approach for Synthesis of Integrated Palm Oil Processing Complex. Part 1: Single Owner. Industrial & Engineering Chemistry Research 52, 10206–10220.

Ng, R.T.L., Ng, D.K.S., Tan, R.R., 2015. Optimal Planning, Design and Synthesis of Symbiotic Bioenergy Parks. Journal of Cleaner Production 87, 291–302.

Ng, R.T.L., Ng, D.K.S., Tan, R.R., 2013. Systematic Approach for Synthesis of Integrated Palm Oil Processing Complex. Part 2: Multiple Owners. Industrial & Engineering Chemistry Research 52, 10221–10235.

Ng, R.T.L., Ng, D.K.S., Tan, R.R., El-Halwagi, M.M., 2014. Disjunctive Fuzzy Optimisation for Planning and Synthesis of Bioenergy-based Industrial Symbiosis System. Journal of Environmental Chemical Engineering 2, 652–664.

Ng, W.P.Q., Lam, H.L., Yuen, F., Kamal, M., Lim, J.H.E., 2012. Waste-to-wealth: Green Potential from Palm Biomass in Malaysia. Journal of Cleaner Production 34, 57–65.

Nishida, N., Stephanopoulos, G., Westerberg, A.W., 1981. A Review of Process Synthesis. AIChE Journal 27, 321–351.

NREL, 2011. Biomass Research - Glossary of Biomass Terms [WWW Document]. URL http://www.nrel.gov/biomass/glossary.html (accessed 2.27.14).

Olsommer, B., Favrat, D., Spakovsky, M.R. Von, 1999a. An Approach for the Time-dependent Thermoeconomic Modeling and Optimization of Energy System Synthesis, Design and Operation Part II: Reliability and Availability. Int.J. Applied Thermodynamics 2, 177–186.

Olsommer, B., Favrat, D., Spakovsky, M.R. Von, 1999b. An Approach for the Time-dependent Thermoeconomic Modeling and Optimization of Energy System Synthesis, Design and Operation Part I: Methodology and Results. Int.J. Applied Thermodynamics 2, 97–114.

Osyczka, A., 1981. An Approach to Multicriterion Optimization for Structural Design. Defense Technical Information Center.

Panjeshi, M.H., Tahouni, N., 2008. Pressure Drop Optimisation in Debottlenecking of Heat Exchanger Networks. Energy 33, 942–951.

Papalexandri, K.P., Dimkou, T.I., 1998. A Parametric Mixed-Integer Optimization Algorithm for Multiobjective Engineering Problems Involving Discrete

Decisions. Industrial & Engineering Chemistry Research 37, 1866–1882.

Papaulias, S.A., Grossmann, I.E., 1983. A Structural Optimisation Approach in Process Synthesis - I Utility Systems. Computers & Chemical Engineering 7, 695–706.

Peters, M., Timmerhaus, K., West, R., 2002. Plant Design and Economics for Chemical Engineers. McGraw-Hill Science/Engineering/Math; 5 edition.

Pezzini, P., Gomis-Bellmunt, O., Sudrià-Andreu, A., 2011. Optimization Techniques to Improve Energy Efficiency in Power Systems. Renewable and Sustainable Energy Reviews 15, 2028–2041.

Pistikopoulos, E.N., Ierapetritou, M.G., 1995. Novel Approach for Optimal Process Design under Uncertainty. Computers & Chemical Engineering 19, 1089–1110.

Ponce-ortega, J.M., Al-thubaiti, M.M., El-Halwagi, M.M., 2012. Process intensification: New understanding and systematic approach. Chemical Engineering & Processing: Process Intensification 53, 63–75.

Probiopol, 2014. How is Biogas Used? [WWW Document]. URL http://www.probiopol.de/7_How_is_biogas_used.48.0.html (accessed 5.14.14).

Rad, M.P., Khoshgoftar Manesh, M.H., Rosen, M.A., Amidpour, M., Hamedi, M.H., 2016. New Procedure for Design and Exergoeconomic Optimization of Site Utility System Considering Reliability. Applied Thermal Engineering 94, 478–490.

Rafferty, K.D., 1998. Absorption Refrigeration. Geo-Heat Center BULLETIN.

Rebennack, S., Kallrath, J., Pardalos, P.M., 2011. Optimal Storage Design for a Multi-Product Plant: A Non-convex MINLP Formulation. Computers & Chemical Engineering 35, 255–271.

Reeb, C.W., Hays, T., Venditti, R.A., Gonzalez, R., Kelley, S., 2014. Supply Chain Analysis, Delivered Cost, and Life Cycle Assessment of Oil Palm Empty Fruit Bunch Biomass for Green Chemical Production in Malaysia. Bioresources 9, 5385–5416.

Rezvan, A.T., Gharneh, N.S., Gharehpetian, G.B., 2013. Optimization of Distributed Generation Capacities in Buildings under Uncertainty in Load Demand. Energy & Buildings 57, 58–64.

Rogers, G.F.C., Mayhew, Y.R., 1964. Thermodynamic and Transport Properties of Fluids SI Units arranged by, 5th ed. Blackwell Publishing.

Romanko, O., Ghaffari-Hadigheh, A., Terlaky, T., 2012. Modeling and Optimization: Theory and Applications, in: Terlaky, T., Curtis, F.E. (Eds.), Modeling and Optimization: Theory and Applications, Springer Proceedings in Mathematics & Statistics. Springer New York, New York, NY.

Rooney, W.C., Biegler, L.T., 1999. Incorporating Joint Confidence Regions into Design under Uncertainty. Computers & Chemical Engineering 23, 1563–1575.

Sahinidis, N. V., 2004. Optimization under Uncertainty: State-of-the-Art and Opportunities. Computers & Chemical Engineering 28, 971–983.

Sanaei, S.M., Nakata, T., 2012. Optimum Design of District Heating: Application of a Novel Methodology for Improved Design of Community Scale Integrated Energy Systems. Energy 38, 190–204.

Sargent, R., 2005. Process Systems Engineering: A Retrospective View with Questions for the Future. Computers & Chemical Engineering 29, 1237–1241.

Savic, D., 2002. Single-objective vs Multi-objective Optimisation for Integrated Decision Support. Integrated Assessment and Decision Support 7–12.

Schaffer, J.D., 1985. Multiple Objective Optimization with Vector Evaluated Genetic Algorithms, in: 1st International Conference on Genetic Algorithms. L. Erlbaum Associates Inc., pp. 93–100.

Schlamadinger, B., Apps, M., Bohlin, F., Gustavsson, L., Jungmeier, G., Marland, G., Pingoud, K., Savolainen, I., 1997. Towards a Standard Methodology for Greenhouse Gas Balances of Bioenergy Systems in Comparison with Fossil Energy Systems. Biomass and Bioenergy 13, 359–375.

Schneider, D.F., 1997. Debottlenecking Options and Optimization.

Schock, R.N., Sims, R., Bull, S., Larsen, H., Likhachev, V., Nagano, K., Nilsson, H., Vuori, S., Yeager, K., Zhou, L., 2012. Energy Supply Systems, in: Global Energy Assessment. pp. 1131–1171.

Seider, W.D., Seader, J.., Lewin, D.R., 2004. Product and Process Design Principles: Synthesis, Analysis, and Evaluation, 2nd ed. John Wiley and Sons Inc., New York.

Shah, N., 1998. Single- and Multisite Planning and Scheduling: Current Status and Future Challenges., in: AIChE Symposium Series: Proceedings of the Third International Conference of the Foundations of Computer-Aided Process Operations. Utah.

Shang, Z., Kokossis, A., 2005. A Systematic Approach to the Synthesis and Design of Flexible Site Utility Systems. Chemical Engineering Science 60, 4431–4451.

Shapley, L., 1953. A Value for n-Person Games, in: Kuhn, H.W., Tucker, A.W. (Eds.), Contributions to the Theory of Games. Princeton University Press, Princeton, New Jersey, pp. 207–317.

Sharifzadeh, M., 2013. Integration of Process Design and Control: A Review, Chemical Engineering Research and Design.

Sikos, L., Klemeš, J., 2009. RAMS Contribution to Efficient Waste Minimisation and Management. Journal of Cleaner Production 17, 932–939.

SINTEF Industrial Management, 2002. Offshore Reliability Data Handbook. OREDA Participants.

Smith, A., Luck, R., Mago, P.J., 2010. Analysis of a Combined Cooling, Heating, and Power System Model under Different Operating Strategies with Input and Model Data Uncertainty. Energy and Buildings 42, 2231–2240.

Smith, R.M., 2005. Chemical Process: Design and Integration. John Wiley & Sons.

Sonar, D., Soni, S.L., Sharma, D., 2013. Micro-trigeneration for Energy Sustainability: Technologies, Tools and Trends. Applied Thermal Engineering 1–7.

Sorin, M., Hammache, A., Diallo, O., 2000. Exergy based Approach for Process Synthesis. Energy 25, 105–129.

Srikhirin, P., Aphornratana, S., Chungpaibulpatana, S., 2001. A Review of Absorption Refrigeration Technologies. Renewable and Sustainable Energy

Reviews 5, 343–372.

Stephanopoulos, G., Han, C., 1996. Intelligent Systems in Process Engineering: A Review. Computers & Chemical Engineering.

Stephanopoulos, G., Reklaitis, G. V., 2011. Process Systems Engineering: From Solvay to Modern Bio- and nanotechnology. Chemical Engineering Science 66, 4272–4306.

Stephanopoulos, G., Westerberg, A.W., 1976. Studies in Process Synthesis—II. Chemical Engineering Science 31, 195–204.

Stojkov, M., Hnatko, E., Kljajin, M., Hornung, K., 2011. CHP and CCHP Systems Today, in: Development of Power Engineering in Croatia. pp. 75–79.

Strouvalis, A.M., Mavromatis, S.P., Kokossis, A.C., 1998. Conceptual Optimisation of Utility Networks Using Hardware and Comprehensive Hardware Composites. Computers & Chemical Engineering 22, S175–S182.

Subrahmanyam, S., Pekny, J.F., Reklaitis, G. V., 1994. Design of Batch Chemical Plants Under Market Uncertainty. Industrial & Engineering Chemistry Research 33, 2688–2701.

Sun, L., Liu, C., 2015. Reliable and Flexible Steam and Power System Design. Applied Thermal Engineering 79, 184–191.

Svensson, E., Eriksson, K., Wik, T., 2015. Reasons to Apply Operability Analysis in the Design of Integrated Biorefineries. Biofuels, Bioproducts & Biorefining 9, 147–157.

Tan, J., Foo, D.C.Y., Kumaresan, S., Aziz, R.A., 2006. Debottlenecking of Batch Pharmaceutical Cream Production. Pharmaceutical Engineering 26, 72–84.

Tan, R.R., Andiappan, V., Kin, Y., Ng, R.T.L., Ng, D.K.S., 2015. An Optimization-based Cooperative Game Approach for Systematic Allocation of Costs and Benefits in Interplant Process Integration. Chemical Engineering Research and Design 106, 43–58.

Tan, R.R., Aviso, K.B., Cruz, J.B., Culaba, A.B., 2011. A Note on an Extended Fuzzy Bi-level Optimization Approach for Water Exchange in Eco-industrial Parks with Hub Topology. Process Safety and Environmental Protection 89, 106–111.

Tan, R.R., Ballacillo, J.-A.B., Aviso, K.B., Culaba, A.B., 2009. A Fuzzy Multiple-objective Approach to the Optimization of Bioenergy System Footprints. Chemical Engineering Research and Design 87, 1162–1170.

Tan, R.R., Lam, H.L., Kasivisvanathan, H., Ng, D.K.S., Foo, D.C.Y., Kamal, M., Hallaler, N., Klemeš, J.J., 2012. An Algebraic Approach to Identifying Bottlenecks in Linear Process Models of Multifunctional Energy Systems. Theoretical Foundations of Chemical Engineering 46, 642–650.

Taskhiri, M.S., Behera, S.K., Tan, R.R., Park, H.S., 2014. Fuzzy Optimization of a Waste-to-Energy Network System in an Eco-industrial Park. Journal of Material Cycles and Waste Management 17, 476–489.

Taskhiri, M.S., Tan, R.R., Chiu, A.S.F., 2011. Emergy-based Fuzzy Optimization Approach for Water Reuse in an Eco-industrial Park. Resources, Conservation and Recycling 55, 730–737.

Tawarmalani, M., Sahinidis, N. V., 2004. Global Optimization of Mixed-integer Nonlinear Programs: A Theoretical and Computational Study. Mathematical Programming 99, 563–591.

Tawarmalani, M., Sahinidis, N. V., 2002. Convexification and Global Optimization in Continuous and Mixed-Integer Nonlinear Programming: Theory, Algorithms, Software, and Applications. Springer Science & Business Media.

The Engineering ToolBox, 2013. Fuel Gases - Heating Values [WWW Document]. URL http://www.engineeringtoolbox.com/heating-values-fuel-gases-d_823.html (accessed 9.17.14).

Umar, M.S., Jennings, P., Urmee, T., 2014. Sustainable Electricity Generation from Oil Palm Biomass Wastes in Malaysia: An Industry Survey. Energy 67, 496–505.

Umar, M.S., Jennings, P., Urmee, T., 2013a. Strengthening the palm oil biomass Renewable Energy industry in Malaysia. Renewable Energy 60, 107–115.

Umar, M.S., Jennings, P., Urmee, T., 2013b. Strengthening the Palm Oil Biomass Renewable Energy Industry in Malaysia. Renewable Energy 60, 107–115.

Vanek, F.M., Albright, L.D., Angenent, L.T., 2012. Energy Systems Engineering: Evaluation and Implementation, 2nd ed, McGraw-Hill Education. McGraw-Hill Education.

Varbanov, P.S., Doyle, S., Smith, R., 2004. Modelling and Optimization of Utility Systems. Chemical Engineering Research and Design 82, 561–578.

Vega, P., Lamanna de Rocco, R., Revollar, S., Francisco, M., 2014. Integrated Design and Control of Chemical Processes – Part I: Revision and Classification. Computers & Chemical Engineering 71, 602–617.

Velasco-Garcia, P., Varbanov, P.S., Arellano-Garcia, H., Wozny, G., 2011. Utility Systems Operation: Optimisation-based Decision Making. Applied Thermal Engineering 31, 3196–3205.

Verderame, P.M., Elia, J.A., Li, J., Floudas, C.A., 2010. Planning and Scheduling under Uncertainty : A Review Across Multiple Sectors. Industrial & Engineering Chemistry Research 49, 3993–4017.

Voll, P., 2014. Automated Optimization-based Synthesis of Distributed Energy Supply Systems. RWTH Aachen University.

Voll, P., Klaffke, C., Hennen, M., Bardow, A., 2013. Automated Superstructure-based Synthesis and Optimization of Distributed Energy Supply Systems. Energy 50, 374–388.

von Neumann, J., Morgenstern, D., 1944. Theory of Games and Economic Behavior. Wiley, New York, NY.

Voudouris, V.T., Ariston Consulting, 1996. Mathematical Programming Techniques to Debottleneck the Supply Chain of Fine Chemical Industries. Computers & Chemical Engineering 20 (Suppl., 1269–1274.

Wakui, T., Yokoyama, R., 2014. Optimal Structural Design of Residential Cogeneration Systems in Consideration of their Operating Restrictions. Energy 64, 719–733.

Wang, G., Feng, X., Chu, K.H., 2013. A Novel Approach for Stability Analysis of

Industrial Symbiosis Systems. Journal of Cleaner Production 39, 9–16.

Westerberg, A.W., 2004. A Retrospective on Design and Process Synthesis. Computers & Chemical Engineering 28, 447–458.

Westerberg, A.W., 1991. Process Engineering, Perspectives in Chemical Engineering, Research and Education, in: ADVANCES IN CHEMICAL ENGINEERING. Academic Press, pp. 499 – 523.

Whalley, P.B., 1992. Basic Engineering Thermodynamics. Oxford University Press.

Wicks, F.E., 1994. Extended Linnhoff Methodology for the Economic Optimization of Cogeneration and Combined Cycle Heat Exchangers, in: Faghri A., Y.M.A. (Ed.), American Society of Mechanical Engineers, Petroleum Division. Publ by ASME, New York, NY, United States, pp. 29–37.

Worrell, E., Biermans, G., 2005. Move Over! Stock Turnover, Retrofit and Industrial Energy Efficiency. Energy Policy 33, 949–962.

Wu, D.W., Wang, R.Z., 2006. Combined Cooling, Heating and Power: A Review. Progress in Energy and Combustion Science 32, 459–495.

Yeomans, H., Grossmann, I.E., 1999. A Systematic Modeling Framework of Superstructure Optimization in Process Synthesis. Computers & Chemical Engineering 23, 709–731.

Yi, D., Han, Z., Wang, K., Yao, P., 2013. Strategy for Synthesis of Flexible Heat Exchanger Networks Embedded with System Reliability Analysis. Chinese Journal of Chemical Engineering 21, 742–753.

Yılmaz, S., Selim, H., 2013. A Review on the Methods for Biomass to Energy Conversion Systems Design. Renewable and Sustainable Energy Reviews 25, 420–430.

Yokoyama, R., Shinano, Y., Taniguchi, S., Ohkura, M., Wakui, T., 2015. Optimization of Energy Supply Systems by MILP Branch and Bound Method in Consideration of Hierarchical Relationship between Design and Operation. Energy Conversion and Management 92, 92–104.

Yoshida, S., Ito, K., Yokoyama, R., 2007. Sensitivity Analysis in Structure Optimization of Energy Supply Systems for a Hospital. Energy Conversion and Management 48, 2836–2843.

Yusoff, S., 2006. Renewable Energy from Palm Oil – Innovation on Effective Utilization of Waste. Journal of Cleaner Production 14, 87–93.

Zafar, S., 2014. Biomass Energy and its Promise [WWW Document]. EcoMENA. URL http://www.ecomena.org/category/biomass-energy/ (accessed 7.2.14).

Zafar, S., 2012. Biomass Wastes from Palm Oil Mills [WWW Document]. URL http://www.bioenergyconsult.com/tag/palm-oil-biomass/ (accessed 5.9.14).

Zhang, D., Samsatli, N.J., Hawkes, A.D., Brett, D.J.L., Shah, N., Papageorgiou, L.G., 2013. Fair Electricity Transfer Price and Unit Capacity Selection for Microgrids. Energy Economics 36, 581–593.

Zimmermann, H.-J., 1978. Fuzzy Programming and Linear Programming with Several Objective Functions. Fuzzy Sets and Systems 1, 45–55.

Zitzler, E., Thiele, L., 1998. Multiobjective Optimization using Evolutionary Algorithms — A Comparative Case Study, in: Eiben, A.E., Bäck, T., Schoenauer, M., Schwefel, H.-P. (Eds.), Parallel Problem Solving from Nature, Lecture Notes in Computer Science. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 292–301.

APPENDICES

[Appendices for this thesis is provided in Volume 2.]