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University of Southampton

Faculty of Engineering and Physical Science School of Electronics and Computer Science

Electricity Balanced Model and Agent

for Community Energy Optimisation

by

Didiek Sri Wiyono

Thesis for the degree of Master of Philosophy

Nov 2019

University of Southampton

Abstract

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The excess or shortage of electricity because of massive penetration of renewable energy generators in the local network needs to be handled. Adopting this perspective, community energy using installed renewable generators should maintain the electricity balance and optimise the use of electricity generations to fulfil the demand (load) as well as reducing cost and generating income.

Besides utilising batteries and retailer settlement, grid-connected community energy can join a local market to trade electricity among communities. Using an agent, community energy seeks to achieve an optimised solution to maintain the electricity balance while maximising benefit. Therefore, an optimisation model is proposed.

To demonstrate the optimisation model, specifically in the market settlement, single sealed bid double auction format is used. By adding some assumptions related to the market response, simulations are run to predict the best price to bid (offer/ask) into the electricity market to achieve maximum payoff. Some experiments were performed to choose the best optimisation strategy, specifically in terms of market response and finding the equilibrium prices for all internal traders.

It showed that using an optimisation agent, community energy can achieve an optimum solution to create a balance profile as well as achieving optimum profits for customers, suppliers and battery owners. By using binary search algorithm, suitable internal selling and buying prices as equilibrium prices for all internal traders can be established after the optimum payoff is calculated.

Extended simulation is run using 2018 community energy data. It can be concluded that our optimisations and market response assumptions are capable to achieve optimum profit for community energy, which can be shown using the optimum payoff; local electricity market and battery have a positive impact to all community members although there are several battery limitations. Our community energy management system ensures positive outcome for all members as well as giving easiness for them in terms of financial settlement because, although our optimisation is running every day, price settlement to all community energy members can be done on a monthly basis. It, thus, becomes an easier approach to all members since they do not have to deal with financial settlement on an hourly or daily basis. In terms of internal selling and buying prices, results approximate to the competitive equilibrium price and, therefore, a very significant impact can be obtained compared to the export tariff and retail price.

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Research Thesis: Declaration of Authorship

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

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	- Wiyono, D. S., Stein, S. and Gerding, E. H. (2016) 'Novel Energy Exchange Models and a trading agent for community energy market', in *International Conference on the European Energy Market, EEM*. doi: 10.1109/EEM.2016.7521196.

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List of Abbreviations

List of Abbreviations

- TOU Time of use
- VCG Vickrey-Clark-Groves
- WT Wind turbine

List of Symbols

List of Symbols

Chapter 1 Introduction

1.1 Background

In many potentially suitable places, such as residential or small-business areas, a variety of incentives are given by the government for developing and using micro renewable energy generators. The incentives allow investors, both private and communities, to use distributed micro renewable energy generators that suitable in budget and capacity (Baldick, 2012; Barthelmie, Murray, & Pryor, 2008; DECC, 2014b). Micro renewable energy generators, such as wind turbine (WT), photovoltaic (PV), bio power and micro hydro, have different characteristics to fossil fuel-based generators, specifically low operational cost as compared to the Fossil fuelbased generators (Barthelmie et al., 2008; Hvelplund, 2006; Menanteau, Finon, & Lamy, 2003; Owen, 2006) and their intermittent supply. WT and PV are also highly dependent on the weather (Bitar, Khargonekar, & Poolla, 2011; Xie & Ilić, 2008), whereas the micro renewable energy generators are usually always on, meaning that the generators are ready to generate electricity at any time; this is another key difference compared to Fossil fuel-based generators.

In local community energy (CE), in which electricity load and supply usually comes from micro renewable energy generators, problems may occur when either the micro renewable energy generators produce more electricity than their need (internal load) or when they have electricity shortage. At the same time, a complementary surplus or deficit (demand) can be experienced by other CEs. CE needs a solution to solve these problems in order to mitigate losses, such as unused electricity or the lack of a local electricity supply when it is needed.

In an isolated network, in which connection with a retailer via grid does not exist, utilising the batteries is one of the best possible options alongside using peer to peer connection to achieve an electricity balance (Mudasser Alam, 2010). In that setting, energy waste may be occurred in which it could not be stored or given to another system.

On the other hand, there exist many CEs which are located inside the distribution network. Consequently, these CEs have connection to the grid, which makes it possible for them to create a connection with the other CEs as well as with the retailers. In this setting, electricity waste may not exist, since every shortage or excess can be settled by the retailers via direct trading, such as a feed-in tariff (FIT) or net metering (export-import) programs. Moreover, it also creates an opportunity for CEs to trade the electricity (Wiyono, Stein, & Gerding, 2016). Thus, managing electricity production excess or shortage while optimising the use of electricity for CE can potentially create profits or reduce costs.

In the electricity market, where suppliers/retailers and customers trade the electricity, in many cases the end customers (users) do not feel a direct impact from electricity price fluctuation. Specifically, they only feel the (bad) impact when the price is too expensive, or the load is on peak, but, in the opposite condition, they usually do not receive any significant benefits.

The terms of the local electricity market, this was introduced as a model that enables participants in the local area to trade for electricity from their local grid (Ilic, Da Silva, Karnouskos, & Griesemer, 2012; Marzband, Sumper, Ruiz-Álvarez, Domínguez-García, & Tomoiagă, 2013; Michail Ampatzis, Nguyen, & Kling, 2014). This is one of several options for handling the problems specifically because of the massive penetration of micro renewable energy generators in the community area (Hvelplund, 2006; Ilic et al., 2012). This market opens new opportunity for local electricity trading among CEs; it also becomes more interesting since many CEs initiative projects have flourished since the early 2000s.

This study aims to investigate the use of batteries and utilising the local electricity market to increase the benefit of CE in a connected grid network. This study also seeks to propose an optimisation model for CEs to achieve maximum benefit from their electricity generation as well as handle the excess or shortage of electricity. CE utilises an intelligent agent to find an optimised solution to obtain maximum profit or minimum cost while maintaining the electricity balance. The solution includes detailed settlement for the batteries, local market and retailer in terms of electricity flow and prices.

The scope of CE can be very limited as it may locate at microgrid level under the smart grid network. Consequently, an understanding of the microgrid and smart grid concepts, objectives and technologies are also very important. One of the most important issues of the smart grid network is achieving a balanced energy profile in addition to managing loads, supplies, and also controlling the flow and quality of electricity (Martin-Martinez, Sanchez-Miralles, & Rivier, 2016; Sabzehgar, 2015; Tuballa & Abundo, 2016).

There are various types of energy management system (EMS) which have been introduced by researchers (Bagherian & Moghaddas Tafreshi, 2009; Serna-Suarez, Ordonez-Plata, & Carrillo-Caicedo, 2015). One such is implemented at home/household level EMS), via, for example, the smart house concept, energy monitoring and control, etc. (Van Dam, Bakker, & Buiter, 2013) . It can also be done by group of customers via group buying or a group of prosumers, which can increase the forecasting generation accuracy (Goncalves Da Silva, Ilic, & Karnouskos, 2014), or even at community level, which may include some customers and prosumers (Muddasser Alam, Ramchurn, & Rogers, 2013; Shamsi, Xie, Longe, & Joo, 2016).

Other works also have been done to address EMS, especially in regard to the penetration of micro renewable energy and distributed generators in a microgrid network without explaining the electricity market model and trading. These are:

- 1. Model Predictive Control to optimise the use of renewable electricity generators in microgrid. This model can lower the total generation cost by directly dispatching the output from renewable electricity generators in order to compensate temporal load variations over pre-defined time (Kou, Liang, & Gao, 2017; Xie & Ilić, 2008).
- 2. EMS concepts that make decisions regarding the best use of the generators for producing electricity, the best schedule of storage system, proper load management and appropriate selling or buying from the local grid (Bagherian & Moghaddas Tafreshi, 2009; Marzband, Sumper, Domínguez-García, & Gumara-Ferret, 2013; Misra et al., 2013; Su & Wang, 2012) .
- 3. Virtual Power Plan concepts in order to handle the negative impacts of increased uncoordinated distributed generators penetration (Chalkiadakis, Robu, Kota, Rogers, & Jennings, 2011; Narkhede, 2013; Othman, 2013).
- 4. Hierarchical frameworks concepts are also proposed by Xu, Jin, Jia, Yu, & Li (2015), classified into master and client levels. At the master level, combined heat and power systems are dispatched to follow the electric and gas tie-line power set-points within the short term. At the client level, the operating boundaries for the combined heat and power and the demand response are generated and transmitted to the upper layer. Another hierarchical framework is proposed by dividing into lower and upper level management; the lower level focuses on an individual microgrid and the upper level is responsible for managing the microgrids and microgrid community level devices. It is executed consecutively from lower level to upper level. The main purpose is to minimise operational cost (Tian, Xiao, Wang, & Ding, 2016).
- 5. Demand side management and demand response concepts are also introduced as a part of EMS from the demand side point of view regarding rescheduling the demand from installed appliances or loads because of the electricity price and network security control. It can also be done by reducing the demand in terms of price signal in order to obtain benefit or in securing the network (Aghaei & Alizadeh, 2013; Jaradat, Jarrah, Jararweh, Al-Ayyoub, & Bousselham, 2014; Mohsenian-Rad, Wong, Jatskevich, Schober, & Leon-Garcia, 2010; Nguyen, Song, & Han, 2012; Spees & Lave, 2007).

We will describe microgrid, smart grid, EMS, Household EMS, Group Buying, CE, virtual power plan, demand side management and demand response in more detail i[n Chapter 2](#page-28-0)

This study focuses on proposing a model for CEs to maintain electricity balance and achieve maximum benefit. The optimisation is done by an intelligent agent as a part of a community energy management system (CEMS). This study considers load and generation predictions, battery use and the connection to a grid which has connections to a retailer and the local electricity market.

1.2 Problem Statement

First is the need of CEMS to handle the excess or shortage of electricity because of massive penetration of micro renewable electricity generations in their local areas. This is followed by investigating the battery model, retailer model and market model in terms of electricity flow to create a balanced profile of CE.

As well as the ability to handle the excess or shortage of electricity, our proposed solution should also give optimum benefit from the electricity generation to the community. This will be done by utilising an agent. The optimisation is run in different settings in order investigate the benefit of utilising battery and local market besides the existence of a retailer.

With regard to the market settlement, this is not part of our study focus since it is already outside our CE. In this work, our CE is only a part (member) of a local electricity market. We choose to follow double auction market since we assume that many sellers and buyers can be involved in this market. Single sealed bid double auction is also chosen (as an example in our simulation) to facilitate all participants, since they only need to make a single sealed bid regarding the price and quantity of electricity to trade. Consequently, in this work, we need to investigate the best bid or ask price to achieve maximum benefit.

It is understood that, in the market, a successful transaction does not only depend on our bid or ask price, but also depends on other factors, such as quantity of supply or demand and prices. In this study, we add some assumptions regarding the market's response to our bid/ask. Using these assumptions, the best price to bid/ask to achieve maximum benefit needs to be calculated to measure the impact of utilising battery, local market and retailer.

According to economics, market efficiency can be reached through competition when the market reaches a competitive equilibrium. Although in our CE we use centralised control and not the internal competition, after finding the optimum payoff (minimum cost for deficit profile or maximum benefit for surplus profile), we seek to find an equilibrium price close to the competitive equilibrium price. We also include battery fee for using the battery in the optimisation processes. This equilibrium price can be used to pay the internal suppliers (micro renewable energy generators owners), battery owners and bill the internal customers.

1.3 Research Objectives

This study focuses on designing an agent as a part of CEMS to optimise the benefit of local electricity generation. Besides optimising benefit, the agent should perform an important task for maintaining electricity balance to help the microgrid/smart grid network. The detailed objectives of this work are:

- 1. Investigating the models and constraints of battery, retailer and market settlement to achieve a CE's electricity balance.
- 2. Using previous models and constraints, creating an optimisation formula to achieve maximum profit for CE.
- 3. Investigating the best bid/ask price to be used in the market settlement order to achieve maximum profit.
- 4. From the simulation results, finding the impact of utilising battery and local market, specifically in terms of profit gained.
- 5. Finding equilibrium prices which satisfy all members of the community, whether they are customers, battery owners or renewable electricity generators owners.

1.4 Research Contributions

As the first contribution of this work, we develop an optimisation model for CE which is located in the distribution network and maximise the benefit of its local electricity generation. Using the optimisation formula, we also explain the role of battery in CE, specifically when the CE has connections with the retailer and local electricity market. Furthermore, we also consider the role of the local electricity market in terms of creating a balanced electricity profile and new opportunity to trade. Using specific double auction market setting and assumptions, we also find some strategies in terms of how CE can obtain optimum benefits. Finally, we also find an equilibrium price using those assumptions and strategies that satisfy all members in the community. Using these prices, we show that all members in the community can obtain more economic benefits by using this model of CEMS.

1.5 Report Structure

The report is divided into a literature study; CE model, optimisation and experiment; CE data, optimisation and result; analysis and discussion; conclusion and suggestion for future work. The chapters in this report are structured as follows:

Chapter 2 provides knowledge background and previous highly related researches crucial to this study. The knowledge background and previous research are mostly about smart grid, EMS (including virtual power plan), demand side management, demand response concepts in EMS. Market setting, electricity trading and electricity market within the community are also explained.

Chapter 3 contains the main issues of our proposed work. The block diagram model of CE profile and CEMS optimisation are explained. It also provides variables data flow between entities, which creates CE profile and CE optimisation. CE data load, generation and profile data for experiments are presented, followed by a step-by-step optimisation experiment. Final settlement, including finding equilibrium prices for all CE members and investigating the impact of optimisation and battery, is also explained in detail. Determining the best strategy for each type of CE is also included in this chapter.

In Chapter 4, load and generation data patterns as inputs of CE data for our simulation are described. In this chapter, we run simulation and optimisation according to the previous experiments' results. Finding equilibrium prices for internal customers and suppliers, as well as comparing the prices with export tariff and retail price in order to show the impact of using our CEMS, are also presented.

Analysis and discussion about our findings from experiments and simulation are discussed in Chapter 5, while Chapter 6 states the conclusion and suggestions for future work for this study.

Chapter 2 Literature Study

In this chapter, smart grid, EMS (including virtual power plan), demand side management, demand response concepts in EMS, market setting, electricity trading and electricity market within the community are explained along with some previous related research study. The explanation and samples are mainly to support our knowledge for discussing our proposed CEMS models.

2.1 Smart Grid and Energy Management System

In this section, smart grid and EMS are briefly introduced. In terms of smart grid, we provide an overview of smart grid, the hierarchical model of smart grid technology, control and communication system as well as business opportunity and profit model to provide a clear understanding of how the smart grid works technically and commercially. We also provide a short overview of EMS, including examples of EMS using several technologies, such as virtual power plan and demand side management, including demand response as well as describe EMS using MAS and game theory point of view. Some related works are briefly explained in this segment.

2.1.1 Microgrid and Smart Grid

The Consortium for Electric Reliability Technology Solutions (CERTS) in the USA introduced microgrid as 'an aggregation of loads and micro-sources operating as a single system providing both power and heat'; however, there is a slight difference of concept to the EU approach. T*he European MICROGRIDS project* defines microgrid as a low voltage distribution network comprising various distributed generators, storage devices and controllable loads. It can operate unified or isolated from the main distribution grids (Martin-Martinez et al., 2016).

According to Mariam, Basu, and Conlon (2016), microgrid is seen as an organised power subsystem containing several distributed generators and a cluster of loads. The distributed generators can be a conventional generation and/or renewable, such as photovoltaic, wind power, hydro and fuel-cell devices (Sabzehgar, 2015).

The microgrid concept assumes an aggregation of loads and micro sources (<500kW) operating as a single system. The implementations of microgrid usually have both controllable and uninterruptible loads that contribute to increase the flexibility of the microgrid. The main idea of managing a microgrid is usually to achieve the optimal dispatch of an aggregated group of

different kinds of distributed generators with the final goal of minimising the global energy cost in the microgrid (Celli, Pilo, Pisano, & Soma, 2005).

Smart grid is an intelligent electric grid that integrates the actions of all users connected to it, including both generators and consumers in order to deliver sustainable and secure electricity supplies efficiently (Siano, 2014) as stated by *the Strategic Deployment Document for Europe's Electricity Networks of the Future* (Tuballa & Abundo, 2016). Another definition is provided by *the National Institute of Standards and Technology* (NIST) specifically mentioning varieties of digital computing, ICT and services in two-way communication and control. It may also consist of smart meters for homes and businesses to measure the bi-directional flows of energy.

2.1.1.1 Hierarchical Levels of Smart Grid

Figure 1: Hierarchical Diagram in Smart Grid Network (Martin-Martinez et al., 2016)

Martin-Martinez et al. (2016) proposed hierarchical levels of the smart grid consisting of microgrid, nanogrid and picogrid. The picogrid is considered as an aggregation of manageable loads connected in a household, while the nanogrid is considered as a building grid with micro renewable energy generators and loads. microgrid usually corresponds to households, buildings and neighbourhood electricity networks that can be connected or isolated to the power distribution grid or to another microgrid. In their perspective, the microgrid is usually owned by an energy service provider, which can be an aggregator or a retailer. There is another system running in a microgrid network besides the aggregator management system and which is responsible for energy efficiency and economic exchange, the system is called a microgrid management system from the distributed system operator*,* the main function of which is to guarantee stability and security in the network.

As a controllable entity within the power system which can work as a single load or supply, Mariam et al. (2016) stated that the advantages of the microgrid from the customer point of view are:

- 1. Microgrid can meet their electrical requirement locally and supply uninterruptible power
- 2. Microgrid can improve local reliability, reduce feeder losses and provide voltage support
- 3. Microgrid can reduce environmental pollution and global warming through utilising lowcarbon renewable electricity generators

2.1.1.2 Control and Communication System

There is a multi-layers control model in the microgrid network (Martin-Martinez et al., 2016; Sabzehgar, 2015) and control strategies can be generalised into three different levels including primary (or local), secondary (or power management), and tertiary (or optimisation) control level.

- 1. Primary control is based on local measurements and, thus, no communication is needed. The method of primary level of control is based on inverter output and power sharing control.
- 2. Secondary control can be based on centralised or decentralised control. Model Predictive Control is an example of a centralised control approach (Karagiannopoulos, Vrettos, & Zima, 2014; Kou et al., 2017; Xie & Ilić, 2008) and the majority of decentralised control methods are developed based on multi-agent systems (MAS) (Eddy & Gooi, 2011; Hernandez, Canesin, Zamora, Martina, & Srivastava, 2013; Hernandez et al., 2013; Raju, Milton, & Morais, 2016; Oliveira, Pinto, Praca, Vale, & Morais, 2013; Tomar & Singh, 2015). A fast and reliable communication systems standard is needed for centralised control approaches, while a power management strategy is needed to coordinate the power flows among the different energy sources within a stand-alone grid consisting of various renewable electricity generators.
- 3. Tertiary control is based on a double-layer coordinated control approach including the schedule layer and the dispatch layer (Jiang, Xue, & Geng, 2013). This type of control is proposed for efficient and economic microgrid operation. Usually, a multi-objective cost function, including the operational cost of distributed generators, start-up and shut-down costs for conventional distributed generators, and the cost of interrupted loads are optimised. In addition, minimising the carbon emissions, especially those coming from the gas turbines, is included. The objectives of tertiary control are microgrid construction and operational cost, reliability cost, utilisation of renewable electricity generators, and emission reduction.

2.1.1.3 Business Opportunities and Profit Models

According to Martin-Martinez et al. (2016), there are several threats and opportunities in business for the distributed system operator, retailer, investor and aggregator resulting from microgrid technology and the penetration of renewable electricity generators. These are:

- 1. The distributed system operator and retailer will face lower revenues because the increasing tariffs cost in networks' reinforcements will provoke the adoption of more renewable electricity generators and changes in consumer behaviour. It also causes further increment of tariffs for the remaining clients to cover costs, which makes it even more disadvantageous for retaining consumers.
- 2. The retailers and distributed system operator can offer services to customers through an aggregator, which attempts to improve their benefits. This can be done by giving incentives to motivate changes in the consumption patterns of the consumers, which will improve the amount of energy savings
- 3. Retailers and distributed system operator can offer cooperation to create partnerships with investors to run the business in an aggregation of renewable electricity generators, distributed balancing services and active networks management.

According to Ma, Liu, Zhang, Tushar, and Yuen (2016), the aggregator can receive profit or commission from electricity trading, customers can reduce their electricity bills and prosumers can increase their utility by gaining more income from excess electricity production, reducing cost for buying electricity when needed and the subsidy of renewable electricity generator generation from the government scheme through programmes such as Feed-in-Tariff (FIT). Further information about FIT can be found in Ofgem (2016).

According to the several literatures above, our CE can be seen as a microgrid rather than picogrid or nanogrid. CE can coordinate with the distributed system operator and the retailer to become an aggregator to handle CEMS using an agent that optimises the use of their energy generation while maintaining CE internal balance. Our CEMS model can help microgrid management system to achieve internal balance while achieving optimum benefit for the community itself.

2.1.2 Energy Management System

EMS allows monitoring, analysing and controlling the use of energy in a small area and is equipped with sensors, switches, controls and algorithms (Siano, 2014). EMS may consist of a variety of operational practices and control strategies using the hardware and software to maximise the benefit of smart grid. EMS is also highly-related to the optimal allocation of renewable electricity generators and demand reactiveness.

In addition to minimising emissions and system losses, EMS can handle logic and control for islanding and reconnecting the microgrid to the grid network. However, EMS should understand about energy prices, weather prediction, load prediction and also characteristics of the network before managing the microgrid (Celli et al., 2005).

Principally, there are high and low levels control in EMS. In the high level, controls are related to the optimisation problem statement and solution using software, whilst low level controls are related to microgrid's power electronic interface operation using hardware (Serna-Suarez et al., 2015).

2.1.2.1 Energy Management System Using Virtual Power Plan

Virtual power plan mainly consists of a cluster of distributed generators, including micro renewable energy generators (REGs) installations (Aloini, Crisostomi, Raugi, & Rizzo, 2011) that operate independently, but can be aggregated and managed as an imagined generation plant (Hernandez et al., 2013; Nikonowicsz & Milewski, 2012; Othman, 2013; Vale, Pinto, Morais, Praca, & Faria, 2011). Virtual power plans can manage their generation schedule and operating cost in accordance with the demand characteristics (Chalkiadakis et al., 2011; Lloret & Valencia, 2013).

Figure 2: Virtual Power Plan Block Diagram

Generally, virtual power plan facilitates the integration of new smart devices and distributed energy resources s into the electricity wholesale market (Vale et al., 2011) and, nowadays, virtual power plan may run in a local market inside the microgrid system to support or service an EMS. Besides distributed generators, a virtual power plan can also include controllable loads and storage systems.

One example of a virtual power plan solution to the power scheduling problem is proposed by Aloini et al. (2011) who state that, after the internal optimisation problem is solved, the EMS finds the optimal power flow values. Furthermore, the EMS also decides the amount of energy which should be produced and by whom any surplus energy should be stored, or that stored energy should be supplied to the grid/loads and by which storage system energy should be bought or sold from the grid, also which controllable loads should be connected or disconnected.

According to Lloret and Valencia (2013), the virtual power plan concept can be split into a technical or commercial perspective. The former secures and manages optimal operation of the system in line with the physical constraints and technical aspect., while in the latter the virtual power plan focuses on economic optimisation. It maximises revenues for the renewable electricity generators, complying with their technical and economical parameters and usually creates an optimised bid/offer table. Once bids are accepted, the virtual power plan controls contract execution based on the accepted bids.

Figure 3: Simple Virtual Power Plan Model (Othman, 2013)

To optimise the virtual power plan, two negotiation schemes can be run (Vale et al., 2011):

- 1. Internal negotiation, which occurs between operators and aggregate members. It considers forecasted generation of all producers and their expected prices.
- 2. Negotiation among neighbourhood virtual power plans; this happens when the virtual power plan cannot fulfil the consumption need from its inside generation. virtual power plans can choose the best deals for balancing their consumption and production by buying or selling electricity. This can be practised by the next electricity market model.

The virtual power plan's optimisation schemes cannot be implemented in CEMS since we have assumed that CEs only use renewable electricity generators. Consequently, the energy generation from renewable electricity generators is intermittent and highly dependent on weather, as mentioned in Sectio[n 1.1.](#page-22-1) Furthermore, we can only manage to achieve energy balance when there is excess or shortage of our electricity production in CEMS rather than creating renewable

electricity generators scheduling by turning it off when there is surplus of energy, which only causes potential loss from electricity generation.

2.1.2.2 Energy Management System Using Demand Side Management

Demand side management is considered as an interaction between retailer and consumers in which a retailer can control the energy consumption at the consumers' side. The aim is in flattening power consumption (Yuan, Hang, Huhns, & Singh, n.d.) by providing energy-efficient equipment, encouraging energy-aware consumption and giving lower price to consumers to shift their consumption to hours during off-peak time (Mohsenian-Rad, Wong, Jatskevich, & Schober, 2010; Saad, Han, & Poor, 2012).

The interactions between retailer and consumers can be implemented at both social and technical levels. In the former, demand side management is in the form of service agreements between the retailer and their consumers (Karnouskos, 2011), while interactions between smart meters and the retailer control centre is the technical level of demand side management.

The demand side management must fulfil the requirements in three important aspects, such as: market driven, environment driven and network security driven (Aghaei & Alizadeh, 2013). By fulfilling these three important aspects, a demand side management can be implemented successfully. Implementing an efficient demand side management scheme involves a variety of challenges, such as formulating pricing schemes that enable efficient peak load shifting (Kahrobaee, Rajabzadeh, Soh, & Asgarpoor, 2014), implementing scheduling schemes for appliances (Jaradat et al., 2014; Mohsenian-Rad et al., 2010; Wijaya, Papaioannou, Liu, & Aberer, 2013), and monitoring and shaping consumer behaviour (Yuan et al., n.d.).

The essence of demand side management spins around the interactions between various entities with specific objectives. At this point, game theory (Mohsenian-Rad et al., 2010; Nguyen et al., 2012) and MAS can play an important role (Kahrobaee et al., 2014; Karnouskos, 2011; Ramchurn, Vytelingum, Rogers, & Jennings, 2011).

2.1.2.3 Demand Response in Demand Side Management

The Federal Energy Regulatory Commission (FERC) has stated that demand response is the ability of customers to reduce their electricity consumption because of either a reliability trigger or a price trigger from their retailer, load-serving entity, regional transmission organisation, or demand response provider (Aghaei & Alizadeh, 2013). Usually, demand response happens when customers receive an energy price signal and the customers respond because they have been given an incentive payment (Aghaei & Alizadeh, 2013; Ali et al., 2015; Cappers, Goldman, & Kathan, 2010; Deng, Yang, Chow, & Chen, 2015; Siano, 2014).

The mechanism is by reducing the energy load (consumption) when the real-time price is high. Because of supply and demand pattern, some retailers mostly use time of use (TOU) tariff. In TOU, the price is high when there is peak load or minimum supply, and vice versa. Without a TOU pricing scheme, customers will not respond by reducing their consumption because they cannot obtain any benefit from demand response.

There have been many recent researches into designing demand response as a part of demand side management, (Jin, Feng, Liu, Marnay, & Spanos, 2017) proposing microgrid optimal dispatch demand response to involve customers, prosumers with renewable electricity generators and the grid securing mutual benefits by using a multi-objective trade-off. The authors contribute a potential cost saving using accurate forecasters when dealing with the uncertainty of electric price and supply from renewable electricity generators. They also demonstrate the demand response potential and utility-cost trade off, showing both peak reduction and cost saving. Vrettos, Oldewurtel, Vasirani, and Andersson (2013) studied demand response to minimise balancing energy cost in the electricity market. Direct control and price-based control concepts are used to control aggregate pool. The centralised control showed better result than the decentralised control but requires a large communication burden and arises privacy issues.

Although, in general, demand side management and demand response can be implemented parallel with our CEMS, they will only take part after we have completed our optimisation. Specifically, demand side management can be run when it is dealing with network security driven, as mentioned above. It can be run after service agreements are signed between CE and the retailer and demand response can be run if they both agree to use a TOU tariff.

2.1.2.4 Multi Agent System and Game Theory in Energy Management System

Multi-agent system (MAS) can be defined as a loosely coupled network of agents that work together to solve problems that are beyond the individual capabilities or knowledge of each problem solver. The agents are autonomous and may be heterogeneous in nature (Jennings, Sycara, & Wooldridge, 1998). Many researchers have studied the use of MAS in EMS. Hernandez et al. (2013) presented MAS model for virtual power plan. In this model, a new power plant concept consists of cooperation of smaller and intelligent generators rather than a big installation. Not only focused on the management of the different elements, this model also includes a set of smart agents for collaborative forecasting of disaggregated energy demand of domestic end users. Several researches have been undertaken regarding designing the automation and optimisation of EMS in smart grid using MAS (Raju, Appaswamy, Vengatraman, & Morais, 2016; Raju, Rajkumar, & Appaswamy, 2016; Raju et al., 2016) . They implemented their design using Java Agent Development Environment. Using the simulation, they concluded that microgrid can
achieve economic and environment optimisation. Carvalho, Perez, and Granados (2012) proposed a MAS approach based on reinforcement learning strategy to manage the energy supply and reducing cost from power losses from non-renewable electricity generators.

From the above previous research, we can assume that MAS is widely used in EMS to capture the real system model, which consist of many entities interacting to achieve their individual goals.

Nguyen, Kling, and Ribeiro (2013) used cooperative game theory to obtain an optimal allocation for resources and in solving the conflict of interest between renewable electricity generators to achieve an optimal electricity supply system, while a game theory framework was proposed by Nguyen et al. (2012) to model independent decision-making of users' energy consumption scheduling. Here, a distributed demand side management algorithm is used to achieve the Nash equilibrium of the game in which each user tries to minimise its energy payment to an energy provider. This algorithm requires only the interaction between the energy provider and users via pricing information. It can reduce the energy cost and peak-to-average ratio of the system compared with the centralised design. Saad, Han, and Poor (2011) proposed the use of coalitional game theory in a microgrid network using cooperative strategies for microgrid networks based on coalitional game theory with allows microgrids to cooperate and form coalitions. The algorithm allows the microgrids to form or break coalitions to minimise the costs incurred by the losses of power over the distribution lines. Such coalition also produces a significant reduction in the power losses. is by Wang, Ouyang, Krishnan, Shu, and He (2015) proposed another EMS based on game theory adopting unified energy management model using a price signal to regulate distributed devices. An algorithm to fairly allocate the losses reduced due to distributed generator participation using game theory is created. To obtain maximum benefits, an iterative method is used to approximate the optimal generation scheme for distributed generators. Furthermore, a demand response mechanism is used to generate a distribution locational marginal price signal as feedback to regulate the distribution locational marginal price. Using simulation, unified energy management model can lead to greater competitiveness as it increases distributed generators' benefits, reduces system losses and improves stability.

Zhou, Bai, and Zho (2015) proposed a *Stackelberg* game approach for EMS is in which a centralised energy management algorithm is used to maximise the total utility of utility companies, microgrids and customers. In this approach, the electricity generation cost, pollutant emission cost and customer satisfaction are taken into consideration. They continued the model by creating a two-stage *Stackelberg* game for the interactions among utility companies, microgrids and customers. Using the simulation, the distributed algorithm could achieve near optimal performance as the centralised algorithm when the number of game iterations was sufficient to ensure the algorithms converge.

Saad, Han, Poor, & Başar (2012) provided a comprehensive overview of game theoretic methods in smart grid. In which they identified the main technical challenges as demand side management problems, specifically communication in microgrid interactions, and discussed how game theory can be applied to handle these challenges, stating that most of the existing works have focused on classical static non-cooperative games.

One of non-cooperative games we mention here is that proposed by Saad et al. (2011) in which they introduced an approach for studying the complex interactions between electric vehicles seeking to sell part of their stored energy surplus to an smart grid. A non-cooperative game between them is proposed in which each group wants to achieve an optimal utility function that captures the benefits from energy selling as well as the associated costs by strategically calculating the maximum amount of energy that it is willing to sell. A double auctions approach is selected leading to a strategy-proof outcome. To solve the proposed game, they used an algorithm which enables the plug-in hybrid electric vehicle groups to reach a Nash equilibrium of the game in a distributed manner.

We show some examples of cooperative games for EMS, one of which is proposed by Saad, Han, and Poor (2011). In this approach, it allows a number of microgrids to cooperate and form coalitions, in order to minimise the costs incurred by the losses of power over the distribution lines. They formulated a coalition formation game between them which allows the microgrids to make decisions on whether to form or break coalitions. It shows that the proposed coalitional game solution yields a significant result.

Another cooperative approach in demand side management was proposed by Yuan et al. (n.d.). They developed a mechanism that reduces peak total power consumption. They encouraged all players to express flexibility in their power consumption and in reporting their preferences truthfully. The mechanism is budget balanced and truthful. Using simulation, the mechanism could largely reduce the computational complexity that the optimal allocation requires, while maintaining approximately the same performance.

A framework for large-scale cooperative electricity consumption shifting to promote the proactive balancing of the demand curve was proposed by Akasiadis and Chalkiadakis (2016) with the formation of agent cooperatives offering large-scale electricity demand shifting services and advancing a complete framework for their operation by only using standard smart meter sand transmission equipment which are readily employed. The mechanism is equipped with internal pricing schemes that employ gain transfers within a cooperative, to make it worthwhile for individuals to participate in shifting operations and guarantee the scheme's effectiveness and profitability. The effective consumption shifting scheme allows for the proactive balancing of electricity supply and demand. Their mechanism possesses individual rationality, truthfulness and

(weak) balanced budget. Based on their results, the methods could deliver tangible benefits to energy cooperatives and other business entities operating in this domain.

From the above descriptions, cooperative or non-cooperative game theoretic approaches can be used in an EMS. In general, the approach selection depends on the design models we created.

Although MAS and game theory have been proven in many cases for EMS, we will not use them in our CEMS since, at this time, we have chosen to only use single agent to perform the optimisation. We will use MAS and game theory in our future work, specifically in dealing with distributing benefit among community members after the optimisation is done. It will more likely use MAS or coalitional game theory.

2.2 Electricity Trading in Smart Grid

Penetration of renewable electricity generators in a smart grid network and capability for prosumers to supply electricity to the grid lead to an energy exchange and trading between smart grid users. The benefits of energy exchange inside smart grid include reducing energy losses of power over the distribution lines and reducing transmission cost, which can create more profit for all players in the microgrid. The following are among the economic motives for players to join energy market trading inside a microgrid:

- 1. Customers could get cheaper energy cost and, therefore, reduce their energy bills.
- 2. Renewable electricity generators owners, both from prosumers and suppliers, could get a better energy selling price.
- 3. The aggregator obtains profit for managing the network.

Many researchers have proposed electricity trading inside the microgrid or between microgrids inside a smart grid network. Neighbourhood trading is proposed by Ilic et al. (2012) who created an energy market based on a stock exchange model. The matching process is based on first-comefirst-served, and every update, received order and cancellation will be sequentially executed. The market has a fixed timeslot, every matched orders in a trading period will be executed, and the unmatched orders are aborted. Nagata, Ueda, and Utatani (2012) proposed an electricity trading in smart grid using a decentralised MAS.

Figure 4: Electricity Trading and MAS in Smart Grid (Nagata et al., 2012)

The negotiation steps are almost the same as Ilic et al. (2012), after announcing the market initiation message to all participants, smart grid control agents (SGC) receivers' sellers agents (SAGs) and buyers' agents. SCG pairs up matched SAG and buyer agent then informs them and this is repeated until SAG and buyer agent combination is complete and then the market is closed.

Rodríguez-Aguilar, Fayol, Saint-Etienne, and Picard (2015) proposed a market that allows prosumers to trade electricity while satisfying the constraints of the grid. An allocation rule is based on an efficient dynamic programming algorithm that assesses in polynomial time how much energy each prosumer trades as well as how energy must be distributed throughout the grid considering the network constraints.

Direct electricity trading between end-users and suppliers was proposed by Lee, Xiang, Schober, and Wong (2014) who analysed cooperation between end-users and suppliers using coalitional game theory. The retailers are eliminated in this direct trade to obtain more benefit for both parties. Specifically, an electricity pricing scheme that achieves a fair division of revenue between suppliers and end-users is analytically derived by using the asymptotic Shapley Value.

Using dynamic matching mechanism, Sikdar and Rudie (2013) proposed a competitive microgrid market. Every individual renewable electricity generator and load meet to create a bilateral energy trade by maximising their bid in accordance with their own strategy. In this mechanism, they do not need to share their reserve price and valuation.

Peer-to-Peer (P2P) electricity trading represents direct trading between peers, where electricity from small-scale distributed energy resources and micro renewable energy generators in dwellings, offices, factories, etc., is traded among the local market. Some scientists use a hierarchical system architecture model to identify and categorise the key elements and technologies involved in P2P energy trading. The results showed that P2P energy trading is able to improve the local balance of energy generation and consumption (Mengelkamp et al., 2018).

A hierarchical energy management strategy for a community of multi smart homes was also proposed by Aznavi, Fajri, and Rasheduzzaman (2018) in which a centralised decision-making unit strategy is selected for reducing the stress on the grid at the point of common coupling. By organising the day-ahead schedules obtained from each household, it minimises the standard deviation of the overall imported energy from the grid. The results showed that the strategy is effective in flattening the grid power profile at point of common coupling, especially during the presence of plug-in electric vehicles.

In our CEMS, electricity trading only happens with the retailer or via the local market. Internally, our CEMS does not facilitate electricity trading among members since it can cause some members to not gain the benefit of their local energy generator when they fail to trade. This issue can lead to CE instability since, according to the CE concept, every member should obtain benefit from their local renewable electricity generators to avoid community objections like the 'not in my back yard' (NIMBY) issue in a centralised renewable electricity generator concept which has happened in many places (Crispim, Braz, Castro, & Esteves, 2014; Sundt & Rehdanz, 2014).

2.2.1 Centralised versus Decentralised Approach

Vrettos et al. (2013) proposed the use of demand response to minimise balancing the energy costs of balance groups (BGs) in electricity markets. Two control schemes are developed based on balancing energy cost reduction in electricity markets with aggregations of large office buildings. Although centralised control shows a performance benchmark, it requires a large communication burden and arises privacy issues. The decentralised approach result shows the opposite. Using the simulation, it shows that there exists a large potential for balancing cost reduction with both control approaches.

A centralised approach in EMS was also proposed by Aloini et al. (2011), specifically by solving the power scheduling problem using optimisation. The EMS as a centre decides several issues such as the amount of energy to be produced, storing surplus energy or supplying energy from storage, buying energy or selling energy to the grid as well as connecting or disconnecting controllable loads to achieve the optimal power flow. The renewable electricity generators, loads and batteries follow the EMS centre decision. Wang, Mao, and Nelm (2013) and Wang et al. (2015) also proposed a centralised approach in optimising EMS. They presented an offline algorithm that can solve the problem with optimal solutions then developed an online algorithm that requires no future information about users and the grid. They proved that the online solution is asymptotically optimal.

Finally, the centralised control structures tend to require more complicated bids from the distributed energy resources s (suppliers) to perform all the necessary calculations to find the optimal dispatch, but the resulting market efficiency is higher than in fully distributed systems. This is mainly because fully distributed systems imply self-interested agents and, consequently, trading strategies towards individuals rather than social benefit.

As mentioned in sub-segmen[t 2.1.1.2](#page-30-0) and in previous research (Aloini et al., 2011; Vrettos et al., 2013; Wang et al., 2013; Zhou et al., 2015), we conclude that both centralised and decentralised approaches have their own competitiveness in CEMS. We try to create a centralised control but seek to rely on continuous hourly updated load and generation predictions and in only using single sealed bid to create market settlement.

2.2.2 Trading Agents and Electricity Trading Models in Smart Grid

One important issue of the smart grid is the ability to autonomously manage the trading of electricity between homes and microgrids. Trading agent is an essential key to run a trading mechanism in such an electricity market. Below are examples of trading agents and electricity trading models that have been proposed by researchers in their previous works.

2.2.2.1 Trading Agent

Vytelingum, Ramchurn, Voice, Rogers, and Jennings (2010) proposed trading agents to automate the trading procedure and implement trading strategies to maximise profit of an individual player. Buyer and seller agents compete in a continuous double auction trading mechanism. In terms of security and online balancing mechanisms, they did not mention any specific agents. However, if these agents existed, they are not directly used in continuous double auction trading mechanism. Salman, Kahrobaee, Rajabzadeh, Soh, and Asgarpoor (2013) modelled smart homes as autonomous trading agents considering the microgrid as a MAS. The randomness of a home's electricity consumption behaviour, wind generation and the grid's electricity rates were considered in this model. The trading agent behaves as an EMS tool for his home. This model worked effectively by indicating how a smart home trading agent should buy, store, sell, or use electricity to minimise cost/bill. Moreover, the trading agent could obtain more benefit by creating interaction with the grid to trade electricity.

Eddy and Gooi (2011) introduced several trading agents in their MAS. Generation Agent is an agent for controlling renewable electricity generator and setting the selling price for trading electricity while Load Agent is an agent for specifying the amount of electricity to buy and

perform trading on behalf of customers. Agents such as monitor, aggregator, control and grid are hired to support the electricity trading in MAS.

Another trading agent was proposed by Nagata et al. (2012). Their smart grid electricity trading system is formed by buying agents, seller agents and smart grid control agent in addition to supporting agents such as generator agents, load agents and grid agent. Smart grid control agent plays an important role in this system as an optimisation centre of the smart grid operation using a specific negotiation algorithm.

After mentioning several trading agents in the microgrid electricity trading that have been proposed by previous researchers, essentially, when using the MAS model, we believe that buyer, seller and market or aggregator agents are needed to give a MAS ability for trading electricity in smart grid. This can be supported with grid agent and control or sensor agents as well as load and generating agents.

Rather than using a specific trading agent, in our CEMS we use a more general agent which can do several tasks to maximise CE benefit, including electricity trading with the local market. In the market settlement, which will be explained later, the agent will perform as trading agent specifically to achieve maximum benefit from the market settlement process.

2.2.2.2 Electricity Trading Models

Previous proposed researches have been done regarding electricity trading models in smart grid. One of these is the point/reward based trading model proposed by Mihaylov, Jurado, and Moffaert (2014) in whose model prosumers are billed by the retailer in accordance with their actual usage and rewarded based on their actual energy input. The mechanism achieves demand response by providing incentives to prosumers to balance their production and consumption out of their own self-interest. NRG coin is used in dealing with rewards and payments.

An interactive demo that illustrates the performance of their model for trading energy called *NRG-X-Change* is proposed (Mihaylov et al., 2015). Participants can interact with the demo by playing with energy consumption and production and analysing in real-time the behaviour of the energy market and, in turn, the price for NRG coin.

Dynamic matching trading by *NOBEL market* is based on the *stock exchange* model but using discrete fixed-sized timeslots throughout a day. A day ahead timeslots are used to trade energy by booking for a timeslot. In this market, all participants should have capability to predict their electricity demand/supply for a specific timeslot. Every order represents each unit price and the quantity for both demand and supply. Traders can revise orders caused by any prediction deviation. The revised order can be caused by dynamically changing behaviours or weather but

can be considered only if the timeslot is still open. The matching process will be repeated every time a new order is received; therefore, single order may partially match with multiple orders from the slot's set of orders*. Order* represents an acceptable price for each unit of quantity in an order of a trader (Ilic et al., 2012). This type of auction can be termed as a double auction.

Generally, double auction and continuous double auction are suitable for many sellers and buyers (Klemperer, 1999). In continuous double auction , market clears continuously as new orders arrive. Koutsopoulos and Iosifidis (2010) proposed an auction mechanism for network resource allocation; the principle of their auction design is for maximising auctioneer's revenue.

Vytelingum, Ramchurn, Voice, Rogers, and Jennings (2011) discussed automated trading in smart grid without a central control by focusing on the application of micro-storage technology. They developed a market mechanism based on which automatically manages the congestion within the system by pricing the flow of electricity. A continuous double auction -based model may appropriate for the local energy market since it allows participants quickly adapt to the changing conditions that may lead to a better usage of resources (Da Silva, Karnouskos, & Ilić, 2013).

Methenitis et al. (2017) proposed sequential second-price auction and *Vickrey-Clark-Groves* (VCG)-based auction. They adapted service level agreements for smart grid to allocate uncertain power generation to buyers of varying preferences. The sequential second-price auction and VCG mechanisms that allocate service level agreements based on buyer bids are incentive compatible and show that both mechanisms ensure that no buyer has an incentive to misreport its valuation.

Generally, both double auction and continuous double auction can be implemented for local market trading in our simulation. We choose to implement double auction in our CEMS since we will get a simpler way to trade, specifically by assuming to use one sealed bid double auction where every participant in the market, including our CEMS, can only perform single ask/bid to trade before the auctioneer decides the final transactions. On the other hand, if we assume our local market using continuous double auction, in order to get transaction, we may perform more than one ask/bid, which makes it a more complicated task for the agent.

In our future work, we may consider any double auction market model, including continuous double auction, to make our CEMS more applicable for many market settings, while, regarding the internal settlement between community members, rather than using coalitional game theory to handle the benefit distribution, the idea of NRG coin can be adopted.

2.2.3 Local Electricity Market

Several researchers have proposed their model for local electricity trading and market in a smart grid network, which is usually located in a neighbourhood area. Again, the NOBEL project is an

example of a project to design a local energy market, the goal of which is to facilitate and manage electricity trading between people of a smart-city. *NOBEL market* is stock exchange-based and uses discrete fixed-sized timeslots throughout a day. A day ahead timeslots are used to trade energy by booking for a timeslot. All participants should have a good capability to predict their electricity demand/supply for a specific timeslot. Every order represents a unit price and the quantity both for demand and supply (Ilic et al., 2012).

Buchmann, Kessler, Jochem, and Bohm (2013) proposed a model of local energy market by generating a data set that models the supply and demand of energy of a small town. They specifically compared the monetary costs and the $CO₂$ emissions from an anonymised local energy market to an unmodified one. The results show that, for most of the households, the applied methods result in low additional cost, while unusual power consumption profiles may, however, lead to high costs.

Ampatzis, Nguyen, and Kling (2014) proposed their work on identifying the characteristics of the participants of the electricity market for a case study of residential customers with PV generation, residential energy storage and inelastic demand to design a local electricity market based on control for the coordination of distributed energy resources. Self-interested participants are assumed with profit maximisation utility functions, while the auctioneer aims to maximise the total surplus of the market. Their proposed design is based on a continuous double auction with private information; the unmatched bids and asks are served by the grid.

Ali et al. (2015) developed a framework focusing on demand response capability in balancing the market. It consists of two hierarchical stages named energy market stage and balancing power market stage. The energy market stage deals with customers' day-ahead decisions in the energy market, in which the system operator releases day-ahead energy prices and, in response, customers optimise their electricity usage to minimise their expenses. The balancing power market stage optimises customers' intra hour load scheduling decisions. Up/down power regulation incentives are offered to customers who, in the hope of achieving monetary gains, modify their promised day-ahead decisions. The framework allows the customers to make savings in energy expenses as well as the system operator to benefit from demand response.

New terms in the electricity market have been introduced by means of implementing EMS based on market control structure. These terms are micro market and local market. A micro market is an environment over a feeder in a distribution network level which allows all participants consumers, producers and prosumers - to share their energy in a regime of competition. In this market, producers and prosumers send offers and consumers or prosumers send bids, which are matched according to the clearing auction algorithm that also determines the energy prices (Olivella-Rosell et al., 2016). Although a local market sometimes includes a part of a transmission

system, *the European Network of Transmission System Operator for Electricity (*ENTSO-E) stated that, in the local market, there should be no transmission constraints at the market balance areas.

An EU project called *EMPOWER* was established to develop innovative business models and local electricity markets in January 2015. The project encourages micro renewable energy generators and participants to exploit flexibility and create benefit (empowerh2020.eu/, n.d.).

A concept of a blockchain-based microgrid electricity market without the need for central intermediaries has been proposed by Mengelkamp et al. (2018) who derive seven market components as a framework for building efficient microgrid electricity markets. They use the Brooklyn microgrid project as a case study of such a market according to the required components. The case study demonstrated that block-chains are an eligible technology to operate decentralised microgrid energy markets. They mentioned that the use of blockchain technology for electricity transactions makes microgrids more resilient by creating trust between the involved agents, especially with respect to financial payments and electricity delivery.

2.3 Community Energy and Electricity Market within the Community

According the UK's CE guidance (Gov.uk, n.d), *th[e Department](https://www.gov.uk/government/organisations/department-for-business-energy-and-industrial-strategy) for Business, Energy & Industrial [Strategy](https://www.gov.uk/government/organisations/department-for-business-energy-and-industrial-strategy)* defines CE as a community-based project that covers aspects of collective action to reduce, purchase, manage and generate energy. These projects have an emphasis on local engagement, local leadership and control and the local community benefiting collectively from the outcomes.

In the Community Energy Strategy (CES) Report 2014, *the Department of Energy and Climate Change UK* stated that there are more than 5,000 groups in the UK working to transform how their community uses energy. There are four main types of energy activities in CE: generating energy, reducing energy use, managing energy supply and demand and also purchasing energy by collective purchasing or switching to save money (DECC, 2014a). These activities can be implemented by an EMS approach, specifically by using electricity trading by creating an electricity market within the community.

CEs usually focus on renewable energy resources optimisation based on the specific location. Usually, different country/place may have different potential renewable energy resources. In the UK, according to the DECC (2014b), the CE is currently focused largely on using solar PV and onshore wind on their renewable electricity generators.

From the economic point of view, CEM or local electricity markets may exist if there is a significant price gap between selling and buying price within the locations in smart grid network.

According to *Energy UK* (2019), the wholesale cost accounts for only 32% of our electricity bill while other parts of our bill, which increase time by time, are the operational cost, environmental and social policy cost and network costs. These trends will make export tariff from prosumers decrease gradually and create a bigger gap between buying and selling electricity prices.

Mariam et al. (2016) said that, in the wholesale electricity market, the price of electricity is around 0.02-0.04 £/kWh. but the end customers buy the electricity around 0.08-0.14 £/kWh. The price gap is occurred because of the transmission and distribution cost. The loss of energy also makes the cost become higher. Placing renewable electricity generators in a microgrid network will give the opportunity to the suppliers/producers to obtain a higher selling price and help the end customers to obtain a lower buying price. This can occur because the transmission cost and energy losses can be minimised. These facts are important reasons to implement electricity trading between them in CEM.

We identify some other reasons to stimulate the need of such CEM. These are incentives programmes such as Feed-in Tariff (FIT) and Export-Import Scheme (Net metering) in several countries. The FIT and Net metering programmes are designed to stimulate people in installing renewable electricity generators in their local area or premises. Using a FIT programme, prosumers or renewable electricity generators owners can obtain benefits such as generation income for all electricity produced, reduce the electricity bill by using their generated electricity and export income from excess electricity (Butler & Neuhoff, 2008; Ofgem, 2016). Meanwhile, in the Net metering programme, which is still running in Indonesia, every PV prosumer only pays a monthly meter (abonnement) bill and for their net electricity used from the supplier minus their electricity supplied. When their supplied is greater than their used, the offset will become their saving for the next months, as mentioned in Regulation from *the National Electricity Company* (PLN) No. 0733/2013 about Net Metering (PLN 2013).

Considering these facts, we can mention that, by joining a local electricity market such as CEM, the CE can obtain lower prices to buy and higher prices to sell electricity while also supporting the community in using renewable electricity generators. The suppliers/retailers can maintain their business by joining the community, especially in creating partnership in authorising the electricity selling/trading, since there are major barriers to becoming an electricity supplier, with Ofgem's ['Licence Lite'](https://www.ofgem.gov.uk/sites/default/files/docs/2015/04/482_an_introduction_to_licence_lite_factsheet_web_0.pdf.) proving difficult to implement, particularly for prosumers and CE.

In terms of creating CEM, the benefits should cover the whole community, which consist of customers and prosumers as well as CEM investors and the operator in terms of energy or, in this case, electricity. All members should get proportional profit and at least saving on the electricity bill for customers.

As mentioned before, that all community members should get benefit from their local electricity generations, so internal and market settlement should follow the idea. Moreover, we must be aware that, in our community, there are not only prosumers and producers, but also customers who do not have electricity production. In terms of final local price, in our future work we will consider that the price should consider every type of member fairly.

2.3.1 Community Energy Projects and Models

Some CE initiatives projects have been running in the UK and Europe, one of them located in the UK is Local Energy Markets Modelling and Analysis (LEMMA). LEMMA was proposed by Tomlinson et al (2013) from *Swanbarton Limited* and *IPL Limited*. This project ran from August 2012 to May 2013. They investigated trading arrangements for electricity generated from renewable electricity generators, characterised by the presence of consumer and supplier as trading parties located on the same low voltage feeder.

According to Tomlinson, Cainey, Price, and Handford (2013), by offering direct trading that matches local demand to local supply, all parties get economic benefit. The other benefits are increasing the energy efficiency and quality. Following this project, Tomlinson (2015) proposed another project called Exploiting Storage through an open market (EXSTORM) that was shown at the Community Energy Conference 2015 in Bath. EXSTROM demonstrated how a CEM worked in incorporating electricity storage. A real time, P2P markets work with different kinds of trading heuristics and energy prices set mutually between households or small businesses (Tomlinson, 2015).

Another similar project located in Bornholm Island Denmark is *the EcoGrid*. Nikonowicsz and Milewski (2012) observed that EcoGrid introduces the concept of distributed local energy market. The main idea is to put the end-user as the main role of the power market and provide the system operator with the most cost-effective solutions as an EMS. The project shows how an existing energy system with a high share of intermittent and distributed generation can cope with many of the challenges, such as real-time price and direct control, using rapid demand response.

Figure 5: The Architecture of EcoGrid (Jorgensen, Behnke, & Eriksen, 2014)

From [Figure 5,](#page-48-0) it can be explained that the real-time price is set by market operator, which might be the transmission system operator. The transmission system operator decision is because of the need for up-or down regulation due to occurring imbalance generation and consumption and/or limitations in the transmission/distribution system. If no imbalance happens, then the real-time price will be set equal to the day-ahead price. The price is continuously adjusted in response to the predicted price elasticity of the involved market participants (Jorgensen, Behnke, & Eriksen, 2014).

From the point of view of the end-user, current price of electricity is always known, and the enduser can, at any time, take responses such as turning off or on selected appliances. Since the price can potentially change every five minutes, it is better to let automatic end-user "smart controllers" agents make the decision based on their preferences, and, subsequently, control the renewable electricity generators units and/or smart appliances. Relevant information about the electricity production, consumption and prices are informed to the end-user as well. End-user acceptance is crucial for deployment of the smart grids. Only end-users that have signed up for a real-time market contract are subject to the real-time price, so they must sign up for a contract with the supplier which, in turn, handles the final settlement and the financial obligations and risks towards the markets.

The prospects for EcoGrid EU are good by creating a "win-win" situation, enabling small and large electricity customers to reduce their electricity bill, while relieving the power system. This will also reduce investments in grid reinforcements (Gantenbein, Binding, Jansen, Mishra, & Sundstrom, 2012). More information related to the EcoGrid project can be found at [http://eu-ecogrid.net/.](http://eu-ecogrid.net/)

The NOBEL project is another example of a local energy market at smart neighbourhood level. This project was run and assessed in Alginet, Spain, in 2012. The aims were managing the electricity trading between the citizens of a smart city by considering market-driven demand response (Ilic et al., 2012). We have briefly mentioned the mechanism in section 2.2.3.

Texel Energy also ran several CE initiatives in the Netherlands by in 2007; an energy cooperative Ecopower in Antwerp, Belgium, since 2003, and *the Energiegenossenschaft Odenwald eG* energy cooperative in Erbach Germany since 2009 (Avelino et al., 2014). Similar projects are also run in Indonesia, although most of them are initiated by government and companies through grant/nonloan funding. The programmes are called Independent Energy Villages and one of the projects is located in Yogyakarta (Surapranata, 2010).

[Figure 6](#page-49-0) shows how Wiyono et al. (2016) modelled a simple CEM. CEM is an electricity local market within a community. In this model, an auctioneer is needed to manage transaction between traders. The paper introduced two models of CEM energy exchanges. In the first, CEM is only connected to a single source outside the supplier/retailer, which can supply energy and receive energy using the FITs scheme when an imbalance exists between supply and demand, while, for the other model, it has several external connections, such as other CEMs or suppliers/retailers. In the second model, the auctioneer needs to utilise an external trading agent to handle or select suitable transactions with the external entities.

Figure 6: Simple CEM Model (Wiyono et al., 2016)

2.3.2 Community Energy Market Owners and Business Actors

Various CE projects may have different composition of owners, but, generally, we understand all parties become main actors in an electricity market. In creating CEMS, the role of each party has to be taken into account and one of them can be easily removed. By considering all parties, it will avoid refusal in proposing the business model. Local ownership of CE is also a key to help the CE project and CEM be accepted by the community. When the community is not ready financially, investors such as the banking system, private renewable electricity generator or business investors can be invited to create a joint ownership (Pahl, 2012). Several issues, such as not in my back yard (NIMBY) and also profit sharing problems, can be resolved by local ownership (Vaze & Tindale, 2011). To secure the supply, security, and quality issues, CEM needs support from retailers and the distributed network operator.

According to Wiyono et al. (2016), in a simple CEM model, suppliers, demanders and market operator (auctioneer) should be represented as different types of agents along with CEM trading agent, outside supplier/retailer agent, and distributed network operator control agent who will interact with an inside trading agent when imbalance of supply and demand exists. In this work, we adopt Wiyono et al.'s (2016) MAS model.

In general, all the stakeholders should receive benefits by joining the CE. Consequently, the CE optimisation objectives of each of stakeholder are:

- Consumer: Minimise cost of consumed electricity with the constraint of satisfying demand.
- Prosumer: Minimise cost of consumed electricity if PV generation and residential energy storage are not enough for self-consumption. If PV generation and storage are enough for self-consumption, then the objective is to maximise the profit of the energy traded at the local market.
- Supplier: Maximise the profit of the energy traded at the local market.
- Market Operator: Maximise total surplus at each round of the market.

In our CEMS, we still choose a single agent model to do the optimisation. We will adopt our CEM according to Wiyono's (2016) model, specifically for our final settlement between community members where we can assume that suppliers are producers, demanders are prosumers and customers and the market operator is the aggregator itself. By these classifications we will perform CEMS that promise to benefit distribution among members.

Chapter 3 Community Energy Model, Optimisation and Experiment

In this chapter, we propose the CE model, optimisation and some experiments. The CE model includes a brief explanation about generation and load model, CE profile model, battery model, retailer and market settlement model for our CEMS. The optimisation model will include block diagram optimisation and optimisation formula. The CE experiments, which are important to determine the suitable strategy for every type of CE profile data, are also rehearsed. The results will be essential for our CE optimisation and simulation in the next chapter.

3.1 Community Energy Model

We seek to model a CE and discuss how it can be connected to the grid (retailer) or other community energy/external entities to optimise the use of electricity and maximise the benefit. First, we present a CE model and describe the electricity generation, load and storage. In this model, we show how CE optimises the use of electricity.

Community Energy Management System

Figure 7: CEMS Model

Figure 7 describes a CEMS which may consist of few microgeneration units, some loads and a few electric batteries from community members and which are controlled by an agent. CE is located in a smart grid network which has a connection to the grid. In this model, CE can create a peer-topeer connection to another community or join an electricity market for trading the electricity.

Since we assume that our CE can be connected to the retailer, in this model we do not consider any electricity waste. Finally, every surplus can be sold to the retailer using export tariff and every shortage can be fulfilled by the retailer by buying it using retail price.

Figure 8: CE in Local Electricity Market

In our CE, we use an hourly- based electricity model for generations, loads and batteries as well as for electricity export, import and settlement. Let $t \in \mathbb{N}_{\geq 1}^t$. It starts from 1 and runs until 24 for day 1, then continuously from 25 until 48 for day 2 and so on. In daily based, if we use datemonth-year attribute, it can also restart every day. For example: 01/02/2017 runs from 01.00 until 24.00 or 00.00, 02/02/2107 runs from 01.00 until 24.00 and so on. We assume that the optimisation is calculated on a daily basis, and, at the end of each day, the last battery status becomes the initial state of day+1.

To simplify the model, we assume that, in an hourly-based time approach, the electricity flow is constant. For example, if the load at t=1 is 3kWh, it means that, in day 1, it runs from 01.00 until 01.59 and the load is constantly at 3kW.

3.1.1 Generation and Load Model

In our CE, we only use renewable energy sources for our micro generators. Therefore, we assume that our generation model is non-elastic generation. We have two types of generation, from wind turbines and from photovoltaics.

The generation capability refers to the maximum power that the agent expects our generators to generate electricity. Let $wt = (wt_1, ..., wt_t)|wt \in \mathbb{R}^t_{\geq 0}$ denotes the generation capability from wind turbines and $pv = (pv_1, ..., pv_t)| pv \in \mathbb{R}_{\geq 0}^t$ denotes the generation capability from photovoltaics, then the non-elastic generation capability of a CE in t time is denoted by $g =$ $(g_1, ..., g_t)|g \in \mathbb{R}_{\geq 0}^t$ and $g_t = wt_t + pv_t$.

Although there are several kinds of loads, such as shiftable, controllable and critical load (Igualada, Corchero, Cruz-Zambrano, & Heredia, 2014), in our CE we only consider critical (noninterruptable or non-shiftable) load. Considering the household appliances in our CE, specifically in developing countries, the load of a CE in t time is denoted by $l=(l_1,...,l_t)|g\in\mathbb{R}_{\geq 0}^t$

3.1.2 Community Energy Profile Model

The CE profile comes from generation and load. If generation exceeds total load, then the community energy profile is surplus, otherwise, if the generation cannot fulfil the load, then the community energy is shortage or deficit. Let $cp = (cp_1, ..., cp_t)|cp \in \mathbb{R}_{\geq 0}^t$ denote the community energy profile in t time measured in kW where $cp_t = g_t - l_t$.

3.1.3 Battery Model

Naturally, a battery can be characterised by maximum capacity, maximum charging rate, maximum discharging rate and charging/discharging efficiency. To reduce the complexity of our battery model, we assume that charging/discharging efficiency is the same.

Let $s \in \mathbb{R}_{\geq 0}$ denote as maximum energy which can be stored in the battery measured in kW. $Ch_{max} \in \mathbb{R}_{\geq 0}$ denotes maximum charging rate of battery and $DisCh_{max} \in \mathbb{R}_{\geq 0}$ denotes maximum discharging rate of battery. Both charging and discharging rate are measured in kWh. Finally, $e \in [0,1]$ denotes as charging/discharging efficiency of battery. For example, the discharging efficiency is 90% or 0.9. If 2kWh electricity is discharged from battery, only 1.8kWh can be used, the rest is lost as heat. To simplify the calculation, using our example, rather than using 1.8kWh, we use 2.0kWh, but the discharging capacity of our battery is only until 10% capacity remains.

Let $BS = (BS_1, ..., BS_t)|BS \in \mathbb{R}_{\geq 0}^t$ denote the battery status in t time measured in kW where $BS_t = BS_{t-1} - (Disk_t - Ch_t)$.

If the community has more than one battery, which may have different capacity or different charging/discharging rate, then we can model the storages as independent battery for each of them. To simplify the model, we assume that, in our CE, we use identical batteries.

3.1.4 Retailer Settlement Model

In the retailer settlement model, we assume that our community energy can sell or buy the electricity to/from the retailer/grid. Selling is performed using export tariff and buying using retail price. Selling refers to the amount of electricity that the agent sells to the retailer, while buying refers to the amount of electricity that the agent buys from the retailer. The grid settlement refers to the difference between selling and buying.

- Let $\textit{sellG} = (\textit{sellG}_1, ..., \textit{sellG}_t) | \textit{sellG} \in \mathbb{R}_{\geq 0}^t$ denote selling in kWh.
- Let $buyG = (buyG_1, ..., buyG_t)|buyG \in \mathbb{R}_{\geq 0}^t$ denote buying in kWh.
- Let $setG = (setG_1, ..., setG_t)|setG \in \mathbb{R}_{\geq 0}^t$ denote the settlement model, where $setG_t =$ $\text{sellG}_t - \text{buyG}_t.$

In a single timeslot, we only have a single model settlement, which can be selling or buying from the grid. Therefore, in a retailer/grid settlement we will have financial transaction on the grid (FTG) as:

If we sell to the grid,
$$
FTG = SellG \times Expert \,tariff
$$
, otherwise
\nWe buy from the grid, $FTG = BuyG \times Retail \, price$

3.1.5 Market Settlement Model

In the market settlement model, we assume that our community energy can sell or buy the electricity to/from the market. Both selling and buying, we use market settlement price. Selling refers to the amount of electricity that the agent sells to the retailer, while buying refers to the amount of electricity that the agent buys from the market.

- Let $\textit{sellM} = (\textit{sellM}_1, ..., \textit{sellM}_t) | \textit{sellM} \in \mathbb{R}_{\geq 0}^t$ denote selling in kWh.
- Let $buyM = (buyM_1, ..., buyM_t)|buyM \in \mathbb{R}_{\geq 0}^t$ denote buying in kWh.

Other than selling or buying, in this settlement, we also need to understand that the amount of electricity we offer or ask may not be 100% completed by the market. This is fully in accordance with the final decision or clearing by the auctioneer.

In our model, if there is still energy surplus or deficit after market settlement, the final settlement will be done by retailer settlement. The market settlement refers to the difference between selling and buying.

• Let $set{M} = (set{M_1, ..., set{M_t}) \mid set{M \in \mathbb{R}^t_{\geq 0}}}$ denote the settlement model where $set{M_t} = sell{M_t} - buy{M_t}$.

In a single timeslot, we only have a single model settlement, which can be selling or buying from the market. Therefore, in a market settlement, we will have financial transaction on the market (FTM) as:

If we sell to the market, $FTM =$ SellM \times Clearing Price, otherwise We buy from the market, $FTM = BuyM \times Clearing$ Price

3.2 Community Energy Optimisation inside Community Energy Management System

Figure 9: CEMS Optimisation

We focus on balancing the energy using CEMS. A precise allocation is needed to ensure electricity in the CE runs appropriately. The allocation consists of market and retail settlements. In another word, a precise energy allocation must be equal to the community energy profile (cp) . The agent should compute a precise energy allocation, $ea = (ea_1, ..., ea_t)| ea \in \mathbb{R}_{\geq 0}^t$ denotes as a precise CE allocation in kWh.

Given time period i , the precise community energy allocation to an agent depends on battery model, retailer model and market model, as follows:

$$
ea_i = (DisCh_i - Ch_i) + SetM_i + SetG_i, i \in t \text{ where } ea_i = cp_i, \forall i \in t
$$

The surplus and deficit values can be determined using:

if
$$
cp(t) \ge 0
$$
, then $Surplus(t) = cp(t)$, $Deficit(t) = 0$,
else $Deficit(t) = -cp(t)$, $Surplus(t) = 0$.

To capture the performance of our community energy optimisation, we classify our community energy into three types.

3.2.1 Type 1 Community Energy Management System

Type 1 is when CE is not using or not installing batteries and also only connected to the retailer. This type is the simplest one and becomes our baseline model, which only has load, generation and retailer's settlement. In this type, no optimisation can be done since we have no option other than, if there is any surplus or deficit, it will be settled by the retailer using export tariff for selling and retail price for buying. The payoff will be determined by the profile and retailer's prices.

Using *type 1*, hourly pay off or utility (*u*) of our community energy, which comes from buying or selling electricity to the retailer, is:

$$
u(t) = (SellG(t) \times ET) - (BuyG(t)xRP)
$$

Daily payoff or daily utility (μ)

$$
\mu = \sum_{t=1}^{24} u(t)
$$

Subject to constraints:

- 1. ET (export tariff) = $0.04 \frac{t}{kWh}$
- 2. RP (retail price) = $0.14 \frac{t}{kWh}$
- 3. $0 \leq$ Sell $G(t) \leq 198$, $\forall t$
- 4. $0 \leq BuyG(t) \leq 198, \forall t$
- 5. $BuyG(t) = Deficit(t)$
- 6. $SellG(t) = Surplus(t)$

3.2.2 Type 2 Community Energy Management System

Type 2 is when CE is using batteries. These batteries are used to store or to supply the electricity when needed in order to achieve maximum payoff. Using the batteries is a new option which exists in addition to only using retailer's settlement. We can create an optimisation model to achieve the best daily payoff (maximum utility).

Using *type 2*, the formula for calculating utility (u) and daily-utility (μ) of our CE remain the same as *type 1*.

When batteries are used, any surplus or deficit will be settled by utilising the batteries or the retailer using export tariff for selling and retail price for buying. In standard type, we do not have any preferences in using our batteries. Specifically, we are not considering the status of our batteries at the end of the day; they can be any value between full and empty.

In *type 2* our CEMS optimisation (θ) is:

$$
\theta = \max_{Bm(t), Ch(t), DisCh(t), BuyG(t), SellG(t)} \sum_{t=1}^{24} u(t), \forall t \in [1,24]
$$

Added constrains:

- 1. $20 \le Bm(t) \le 200, \forall t$
- 2. $Bs(1) = 100$
- 3. $0 \leq Ch(t) \leq 40$
- 4. $0 \leq DistCh(t) \leq 40$
- 5. $Bs(t) = Bs(t-1) + (0.9 \times Ch(t-1) DisCh(t-1), t > 1)$

Changed constraints

- 1. $BuyG(t) = Deficit(t) DisCh(t)$
- 2. $SellG(t) = Surplus(t) Ch(t)$

In order to use our battery for next day transaction, we must ensure that our battery status is not fully charged or discharged at the end of the day. In our model, we optimise the CE on a daily basis. Since the profile of a day is only available after 00.00 on that day, we need to have space and electricity from our battery to utilise our battery.

We revise our optimisation model for *type 2* by adding a new constraint, which is that, at the end of the day, the batteries' status must be the same as at the initial state. It implies that, although we can charge or discharge the batteries on that day, we need to keep the status of the batteries at the end of the day equal to the status at the initial state.

Added constraint:

1. $Bs(1) = Bs(24)$

3.2.3 Type 3 Community Energy Management System

Type 3 is when CE has another way to settle the electricity imbalance, for example, by trading in the local electricity market. In this type, the optimisation model depends on variables which come from batteries, retailer and also local electricity market property and response.

By utilising this type, we can modify our optimisation model to achieve maximum payoff. It is done by adding the possibility to buy or sell electricity in the local electricity market.

Using type 3, we redefine our payoff or utility as:

 $u(t) = TransM(t) + TransG(t)$

The formula for calculating μ is still the same as before. As there are new variables, such as SellM and BuyM, we redefine our θ as:

$$
\theta = \max_{Bm(t), Ch(t), DisCh(t), BuyM(t), SellM(t), BuyG(t), SellG(t)} \sum_{t=1}^{24} u(t), \forall t \in [1,24]
$$

Added constraints:

- 1. $ET \le$ SellM Price \le RP
- 2. $ET < BuyM$ Price $\lt RP$
- 3. $SellM(t) \leq Surplus(t)$
- 4. $BuyM(t) \leq Deficit(t)$
- 5. $TransM(t) = (SellM Price \times SellM(t)) (BuyM Price \times BuyM(t))$
- 6. $TransG(t) = (ET \times SellG(t)) (RP \times BuyG(t))$

Change constraints:

1. $\text{SellG}(t) = \text{Surplus}(t) - \text{Ch}(t) - \text{SellM}(t)$

$$
BuyG(t) = Deficit(t) - DisCh(t) - BuyM(t)
$$

3.3 Experiment and Simulation

The CE profile data we use for our simulation are based on hourly load and generation data. There are two data samples that we use in this work. The first is generated data using several profile models of CE; these are surplus, deficit and balanced profiles data. We use these first data (experiment data) for simulation of our CEMS approaches. In the next chapter, the second load and generation data from our CE will be presented. The second data pattern we get from [www.elia.be,](http://www.elia.be/) running from 01/01/2018 to 31/12/2018. We will use the second data for strengthening our summary in these experiments. The simulation and the results of our CEMS approach will be analysed and discussed in Chapter 4 as well.

3.3.1 Experiment Data Sample

There are three types of CE profiles in the first data sample which come from 7-days load and generation data. First is deficit profile, when the electricity generations are mostly below the loads, while second type is the surplus profile, when it is the opposite. Third is a balanced profile, which happens when the daily generation and load are almost equal.

Later, we mention the deficit profile data in Experiment 1 as *Exp 1D*, the surplus data in Experiment 2 as *Exp 2S* and the balanced data in Experiment 3 as *Exp 3B*.

Figure 10: CE Load, Generation and Profiles from Experiment Data Sample

In Figure 10, (A), (B) and (C) are representations of deficit CE data, (A) is load data, (B) is generation data and (C) is profile data. It can be seen from the figure that most of the profiles are deficit except for a few days starting from 09.00 until 17.00. (D) is the profile of surplus data and (E) is the balance profile data. Using the profile data (C), (D) and (E), we simulate our optimisations.

3.3.2 Simulation Setting

The simulation setting depends on the CEM type that we have already mentioned in Section 3.2. We use CEM type 1 (no battery, only retailer settlement) as our baseline data. No optimisation can be done since every surplus or deficit can only be cleared by the retailer. We use fixed tariff for selling and buying electricity to the retailer. We set £0.04/kWh for selling to the retailer via FIT or export-import tariff and £0.14/kWh for buying (retailer price). We also use static peak/off-peak

tariff rather than using fixed tariff. We set £0.11/kWh for off-peak and £0.18/kWh for peak tariff. Peak tariff only happens after 16.00 until 20.00 every day.

The FIT prices for export electricity to the retailer can be seen in

[https://www.ofgem.gov.uk/environmental-programmes/fit/fit-tariff-rates,](https://www.ofgem.gov.uk/environmental-programmes/fit/fit-tariff-rates) especially we use proximate mid-price between standard solar photovoltaic receiving the middle rate at £0.0356/kWh and wind turbine rate at £0.0504/kWh. While for retail price, we refer to [https://www.ukpower.co.uk/home_energy/tariffs-per-unit-kwh,](https://www.ukpower.co.uk/home_energy/tariffs-per-unit-kwh) especially we use proximate price combination between fixed safe tariff plus annual meter reading which is around £0.14/kWh. For peak/off-peak tariff, we use static time of use tariff rather than dynamic time of use tariff.

For optimisation 1, 2 and 3, we use CEM type 2. In CEM type 2, we use 10 homogenous batteries each 40kW, max capacity 400kW, min electricity left 40kW. We set maximum charge or discharge 60kWh and battery initial state is 200kWh. Optimisation 1 is only using fixed tariff for selling to and buying electricity from the retailer, while optimisation 2 uses peak/off-peak tariff rather than using fixed tariff. For both optimisations, we use fixed daily based optimisation. This means we consider the load and generation data prediction each day until 24.00. Optimisation is calculated every day at 24.00 to find daily payoff. We extend our optimisation 2 from fixed daily-based optimisation into dynamic 24 hours in advance optimisation, thus it is not daily based. We use it for optimisation 3. In optimisation 3, we always consider 24 hours in advance data load and generation.

CEM type 3 is used for optimisation 4. We also use the same battery setting as the other optimisations. In term of market setting in this CEM, the market is centralised electricity market, operated by an auctioneer. The transaction is hourly based transaction. In the market there are many sellers and many buyers, which follows single sealed bid double auction market. After all buyers and all sellers sent a sealed bid that consist of quantity and price to the auctioneer, the auctioneer clears the market by deciding clearing price using intersection between aggregate supply bids and demand bids. Successful transactions are announced to all traders. Hourly based transaction in the market is considered in order to make the market transactions in-line with our EMS setting.

	CEM model use	Tariffs use	Optimisation periods
Optimisation 1	Type 2 (battery and	Sell: FIT	Fix 24 hour (daily
(C2STF)	retailer settlement only)	Buy: Retail Price	based)
Optimisation 2	Type 2 (battery and	Sell: FIT	Fix 24 hour (daily
(C2POTF)	retailer settlement	Buy: Peak off peak tariff	based)
	only)		
Optimisation 3	Type 2 (battery and	Sell: FIT	Dynamic 24 hour in
(C2POTD)	retailer settlement	Buy: Peak off peak tariff	advance
	only)		(continuous)
Optimisation 4	Type 3 (battery,	Sell: FIT, market selling Price	Dynamic 24 hour in
(C3MPD)	retailer and market	Buy: Peak off peak tariff, market	advance
	settlement)	buying price	(continuous)

Table 1. Optimisations Setting

In optimisation 4 we use several assumptions regarding our bid and market responses. We use the assumptions because we do not investigate real market response in this work. The assumptions are highly essential to run a simulation to get the results. The assumptions are based on a basic economic law, when we offer a commodity in a lower price, we will get more buyers and when we ask a commodity in a higher price then more sellers will offer. We must also be aware that, to avoid losses, the offer must be higher than the export/FIT price and ask prices we use must be below the retailer's price.

Table 2. Assumptions for Optimisation 4

3.3.3 Simulation Result

In this simulation, we calculate daily optimum payoff for all experiments and optimisations. We compare the result and determine which optimisation can get the best payoff. We also investigate the impact of using battery in all optimisations by comparing with no battery installed.

After having comparative results, we try to find internal selling and buying price to all members. We also try to nominate several equilibrium prices for internal suppliers and internal customers. We calculate daily and weekly prices. Since it comes from total payoff, the comparative result between daily and weekly basis does not change the optimum payoff.

We also try to find the simplest way of settlement to all participants which is by using weekly prices rather than daily prices. In the next chapter, after running the simulation for CE data over a whole year, monthly prices and payment will be investigated.

3.3.3.1 Payoff Comparison and Battery Impact

Below are optimum payoff tables from *Exp 1D*, *Exp 2S* and *Exp 3B*.

Day	Op 1	Op ₂	Op 3		Op 4 As 1 Op 4 As 2 Op 4 As 3	
	-85.49	-74.93	-74.88	-73.89	-69.83	-69.11
2	-53.37	-45.74	-44.35	-43.93	-41.41	-40.99
3	-46.19	-41.22	-42.66	-41.95	-39.74	-39.33
4	-58.18	-50.08	-50.08	-49.52	-46.73	-46.26
5	-69.03	-63.23	-54.68	-53.95	-51.00	-50.47
6	-42.50	-34.17	-36.07	-35.88	-33.72	-33.39
7	-49.02	-46.92	-48.56	-47.80	-45.26	-44.78
Total	-403.78	-356.30	-351.30	-346.92	-327.70	-324.33
Rank	6	5	4	3	2	

Table 3. Payoff and Comparison for *Exp 1D* (in £)

Payoff	Op ₁	Op ₂	Op 3		Op 4 As 1 Op 4 As 2 Op 4 As 3	
1	24.42	24.42	24.41	35.40	41.50	36.62
2	15.25	15.23	14.87	21.55	25.27	22.30
3	13.12	13.12	13.52	19.60	22.98	20.28
4	16.62	16.62	16.62	24.10	28.26	24.93
5	19.72	19.72	17.38	25.20	29.54	26.07
6	11.70	11.70	12.22	17.72	20.77	18.33
7	13.66	13.66	15.48	22.45	26.32	23.22
Total	114.50	114.48	114.50	166.02	194.64	171.74
Rank	5	6	4	2		

Table 4. Payoff and Comparison for *Exp 2S* (in £)

Table 5. Payoff and Comparison for *Exp 3B* (in £)

As seen in Table 2, Table 3, and Table 4, better payoff can be obtained by using peak/off-peak tariff rather than fixed tariff. Since the different tariff is only for buying price to the retailers, as long as buying transaction in off-peak time is more than 4/3 in peak time, no matter the daily

profile (deficit or balanced), the result will be better. Compared to Optimisation 1, Optimisation 2 cannot produce better result in surplus profile. This is because the retailer selling price is always the same every time and using battery means some energy losses. Overall, Optimisation 3 results outperform Optimisation 1 and 2, which means that using dynamic 24 hours in advance is better than fixed daily-based optimisation.

As seen in Table 2 and Table 4, using the third assumption (As 3) can lead to better payoff, meaning that bidding or asking around mid-price is the best approach in deficit profile. In surplus profile the best payoff is by using the second assumption, as can be seen in Table 3. We will use the results for a whole year CE data in the next chapter.

Figure 11: Payoff Comparison with No Battery in *Exp 1D*

Figure 12: Payoff Comparison with No Battery in *Exp 2S*

Figure 13: Payoff Comparison with No Battery in *Exp 3B*

Figure 14: Battery Impact in Minimising Cost or Maximising Profit

As seen in Figure 11, Figure 12, Figure 13, and Figure 14, using battery can improve the payoff results in all types of profiles. Regarding the impact on using battery in CE, we can see from Figure 14 that the results are very significant in *Exp 3B* compared to others. In balanced daily profile, the use of battery can be more optimum because the profile is nearly balance and the fluctuations are around the balance. Thus, it can be seen that the battery plays a very important role. We will use the battery (in a same quantity) for bigger load and generation, so the simulation will show that battery quantity cannot charge/discharge in accordance with the deficit or surplus because of battery limitation.

3.3.3.2 Finding Internal Selling and Buying Price

After finding the payoff, we can try to find the internal selling price (ISP) and internal buying price (IBP) as follows:

$$
Payoff(t) = (Gen(t) \times ISP(t)) - (Load(t) \times IBP(t))
$$

Or if we add some battery use commissions (Com), we can extend the equation as:

$$
PayoffB(t) = (Gen(t) \times ISP(t)) - (Load(t) \times IBP(t)) - (Ch(t) \times Com)
$$

For example, if we set Com = £0.01/kWh then the new payoff $(PayoffB(t))$ becomes:

$$
PayoffB(t) = Payoff(t) - (Ch(t) \times 0.01)
$$

There are numerous ISP/IBP pairs according to the increment level (scale). For instance, by taking £0.001/kWh and £0.0001/kWh increments, the amount of ISP/IBP pairs will increase considerably. To reduce the computational time, we set £0.0001/kWh increment scale since it is already highly significant, even if every member has 1000 kWh (in a month).

In order to find the precise prices in a spread between lowest and highest possible price, we use the binary search algorithm.

if
$$
cp(t) \ge 0
$$
, then $IBP = (RT - ET)/2$, else $ISP = (RT - ET)/2$

We use above statement as our baseline ISP and IBP, to find the minimum gap between ISP and IBP. The minimum gap will enable all members to get the equilibrium prices.

To find the gap in a t time $\pi(t)$, the equation is as follow:

$$
\pi(t) = IBP(t) - ISP(t)
$$

We define α as the formula for finding SP and BP which yields minimum π .

$$
\alpha = Min_{BP,SP} \pi(t), \forall d \in R
$$

Optimisation for finding the best price for customers and suppliers applies these constraints.

- 1. $ISP > ET$
- 2. $IBP < RT$
- 3. *if cp*(*t*) ≥ 0, then $IBP \leq (RT ET)/2$, else $ISP \geq (RT ET)/2$
- 4. $IBP \geq ISP$

Figure 15: ISP, IBP and Diff using Optimisation 1 in *Exp 1D*

According t[o Figure 15,](#page-70-0) we can find $ISP = \frac{E0.1369}{kWh}$, $IBP = \frac{E0.1394}{kWh}$, $Diff = \frac{E0.0026}{kWh}$ only at the 5th iteration. Although all ISP and IBP pairs can be used as equilibrium prices, the ISP and IBP with minimum diff can be considered as more competitive prices.

3.3.3.3 Optimisation's impact on Internal Selling Price and Internal Buying Price

Tables 6 to 8 on the next page summarise the ISP, IBP and Diff results from *Exp 1D*, *Exp 2S* and *Exp 3B*, respectively.
Table 6. ISP, IBP and Diff in *Exp 1D* (in £/kWh)

	ISP 1	IBP ₁	Diff 1	ISP ₂	IBP 2	Diff 2	ISP ₃	IBP ₃	Diff ₃	ISP ₄	IBP ₄	Diff ₄	ISP ₅	IBP ₅	Diff ₅
Op 1	0.0900	0.1226	0.0326	0.1150	0.1316	0.0166	0.1275	0.1361	0.0086	0.1338	0.1383	0.0046	0.1369	0.1394	0.0026
Op ₂	0.0750	0.1066	0.0316	0.0925	0.1129	0.0204	0.0838	0.1098	0.0260	0.0881	0.1113	0.0232	0.0859	0.1106	0.0246
Op ₃	0.0750	0.1055	0.0305	0.0925	0.1118	0.0193	0.0838	0.1087	0.0249	0.0881	0.1102	0.0221	0.0859	0.1094	0.0235
Op 4 As 1	0.0750	0.1045	0.0295	0.0925	0.1108	0.0183	0.0838	0.1077	0.0239	0.0881	0.1093	0.0211	0.0991	0.1132	0.0141
Op 4 As 2	0.0750	0.1003	0.0253	0.0925	0.1065	0.0140	0.1013	0.1097	0.0084	0.1056	0.1112	0.0056	0.1034	0.1105	0.0070
Op 4 As 3	0.0750	0.0995	0.0245	0.0925	0.1058	0.0133	0.1013	0.1089	0.0077	0.1056	0.1105	0.0049	0.1034	0.1097	0.0063

Table 7. ISP, IBP and Diff in *Exp 2S* (in £/kWh)

	ISP ₁	IBP ₁	Diff 1	ISP ₂	IBP ₂	Diff ₂	ISP ₃	IBP ₃	Diff ₃	ISP ₄	IBP ₄	Diff ₄	ISP ₅	IBP 5	Diff ₅
Op 1	0.0659	0.0900	0.0241	0.0528	0.0650	0.0122	0.0463	0.0525	0.0062	0.0430	0.0463	0.0032	0.0414	0.0431	0.0018
Op ₂	0.0581	0.0750	0.0169	0.0489	0.0575	0.0086	0.0443	0.0488	0.0044	0.0420	0.0444	0.0024	0.0409	0.0422	0.0013
Op ₃	0.0581	0.0750	0.0169	0.0489	0.0575	0.0086	0.0443	0.0488	0.0044	0.0420	0.0444	0.0023	0.0409	0.0422	0.0013
Op ₄ As ₁	0.0666	0.0750	0.0084	0.0574	0.0575	0.0001	0.0529	0.0488	-0.0041	0.0551	0.0531	-0.0020	0.0563	0.0553	-0.0010
Op 4 As 2	0.0713	0.0750	0.0037	0.0622	0.0575	-0.0047	0.0668	0.0663	-0.0005	0.0691	0.0706	0.0016	0.0679	0.0684	0.0005
Op 4 As 3	0.0676	0.0750	0.0074	0.0584	0.0575	-0.0009	0.0630	0.0663	0.0033	0.0607	0.0619	0.0012	0.0595	0.0597	0.0002

Table 8. ISP, IBP and Diff in *Exp 3B* (in £/kWh)

We can nominate ISP/IBP for each experiment by referring to the best payoff result from Table 3, Table 4 and Table 5. The equilibrium prices must be generated from the best payoff for each experiment to ensure the best result.

According to Table 3, the best payoff in *Exp 1D* can be found in Optimisation 4 with Assumption 3 (Op 4 As 3). Table 6 shows the ISP-IBP pair comparison for each optimisation model in *Exp 1D*. As seen in Table 6, the equilibrium prices are:

$$
ISP = \frac{f0.1034}{kWh}
$$
, $IBP = \frac{f0.1097}{kWh}$ and $Diff = \frac{f0.0063}{kWh}$

ISP4 and IBP4 cannot be used as equilibrium prices because IBP4 is already greater than RT in peak/off-peak tariff.

As seen in Figure 16, the minimum gap is in Op 1, but since the price is exceeding our RP for peak/offpeak tariff, we use Op 4 As 3 results as they are more competitive prices for ISP and IBP. The result, in line with Table 3, is that, in *Exp 1D*, Op 4 As 3 is the best choice.

Figure 17: ISP, IBP pair comparison in *Exp 2S*

According to Table 4, the best payoff in *Exp 2S* can be found in Optimisation 4 with Assumption 2 (Op 4 As 2). Table 7 shows the ISP-IBP pair comparison for each optimisation model in *Exp 2S*. As seen in Table 7, the equilibrium prices are:

$$
ISP = \frac{E0.0679}{kWh}
$$
, $IBP = \frac{E0.0684}{kWh}$ and $Diff = \frac{E0.0005}{kWh}$

As seen in Figure 17, the minimum gap is in Op 4 As 3, but, since the price is not more competitive than Op 4 As 2 results, we do not use it for ISP and IBP. Op 4 As 3 is the best choice, because it is in line with Table 4.

Figure 18: ISP, IBP pair comparison in *Exp 3B*

The best payoff in *Exp 3B* can be found in Optimisation 4 with Assumption 3 (Op 4 As 3) according to Table 5. Table 8 shows the ISP and IBP pair comparison for each optimisation model in *Exp 3B*.

As seen in Table 8, the equilibrium prices are:

$$
ISP = \frac{E0.0772}{kWh}
$$
, $IBP = \frac{E0.0788}{kWh}$ and $Diff = \frac{E0.0788}{kWh}$

Market settlement does not have significant impact on nearly balanced profile, because almost all surpluses and deficits can be handled by utilising the battery.

Based on the results presented in Subsection 3.3.3, we will expand our simulation into one whole year CE data and discuss the overall performance of our model and optimisation in the next chapter.

Chapter 4 Community Energy Data, Optimisation and Results

After presenting our CE setting and profile, this chapter expands our simulation data to calculate the optimum payoff (daily and monthly). We also set out to find the equilibrium price for ISP and IBP using the same method as in Subsection 3.3.3.2, Finding Internal Selling and Buying Price. Finally, we present the benefits for all CE members in terms of cost minimisation or profit maximisation.

4.1 Community Energy Setting

The second data pattern was retrieved from www.elia.be running from 01/01/2018 to 31/13/2018. Using the load data, PV and WT generation data patterns, we create our CE profile as:

- 1. Max Load = 500kW.
- 2. 15 homogenous PV Generators, each having 20kWp electricity generation.
- 3. 12 homogenous WT Generators, each having 40kW electricity generation.
- 4. 10 homogenous Batteries, each having maximum 40kW capacity and 6kWh maximum charge/discharge with 90% efficiency

After downloading the real data from [www.elia.be,](http://www.elia.be/) we calculate the load and generation data pattern from each source. Using the data pattern, we generate our CE according to the profile above.

4.2 Monthly Community Energy Profile

Figure 19 below shows the monthly CE and it can be seen that all profiles are deficit. From the previous chapter, if the profile does not fluctuate, then we cannot hire the battery. The battery can only be useful if there is at least a surplus status between deficit status. On an hourly data basis, profiles fluctuate.

Figure 19: January - June 2018 Load, Generation and Profile

Figure 20: July - December 2018 Load, Generation and Profile

From Figure 19 and Figure 20, we can see that, on a monthly basis, most profiles are deficit. Although we do not show all daily data, to ensure that the optimisation and battery can be used properly, we will show some of daily data that can be seen as hourly fluctuations between deficit and surplus profiles.

Time		01-Jul-18	02-Jul-18	03-Jul-18	04-Jul-18	05-Jul-18	06-Jul-18	07-Jul-18
	$\mathbf{1}$	-164.52	-195.08	-210.60	-366.13	-430.42	-412.04	-411.55
	2	-166.27	-196.72	-211.04	-342.88	-412.69	-403.23	-393.04
	3	-176.64	-216.92	-214.20	-336.03	-398.09	-393.25	-375.90
	4	-203.45	-226.66	-215.95	-351.74	-399.96	-385.94	-367.90
	5	-209.34	-264.36	-237.11	-354.03	-402.89	-385.72	-364.85
	6	-196.38	-267.00	-246.23	-347.59	-396.23	-375.87	-346.31
	$\overline{7}$	-161.68	-257.30	-259.72	-348.18	-385.43	-377.58	-311.48
	8	-109.81	-244.43	-219.14	-333.89	-369.36	-321.43	-251.55
	9	-32.08	-161.47	-160.85	-257.93	-312.41	-255.13	-191.53
	10	48.25	-72.42	-88.59	-205.73	-247.40	-178.03	-139.27
	11	116.62	30.06	-47.18	-148.07	-174.66	-114.29	-91.57
	12	174.99	87.90	-15.38	-97.61	-125.16	-74.96	-44.81
	13	197.66	93.09	19.41	-95.36	-82.39	-61.00	-1.70
	14	186.21	75.68	21.47	-119.33	-64.18	-103.05	18.94
	15	185.65	58.26	-18.98	-172.24	-70.75	-160.58	-14.72
	16	148.22	63.92	-68.71	-185.19	-109.59	-223.30	-72.44
	17	68.47	-0.55	-165.43	-228.44	-162.19	-305.51	-125.58
	18	-41.21	-104.01	-253.60	-308.42	-245.24	-348.20	-196.62
	19	-142.91	-187.39	-306.66	-382.40	-336.84	-380.33	-267.25
	20	-226.74	-255.65	-344.21	-398.40	-407.50	-412.14	-331.88
	21	-269.63	-272.30	-370.93	-425.40	-437.34	-437.12	-364.11
	22	-248.24	-247.05	-369.25	-437.95	-433.46	-428.12	-366.65
	23	-235.64	-236.39	-382.11	-443.23	-445.39	-450.03	-366.65
	24	-219.56	-216.88	-380.45	-448.36	-429.93	-439.02	-358.88

Table 9. Hourly CE Profile Data 01 July – 07 July 2018 (in kWh)

Although surplus profile cannot be observed from weekly-based data in July 2018, as opposed to Figure 20, Table 9 clearly shows that there are fluctuations of deficit and surplus profile in some hours on 1st, 2nd and 3rd July. By these fluctuations, both battery and optimisation can be run more efficiently compared to when there is no fluctuation of profile on 4^{th} , 5^{th} , 6^{th} and 7^{th} July. During those days, the battery cannot be hired.

4.3 Monthly Community Energy Payoff

In Subsection 3.3.3, the best payoff of deficit profile can be found by using Optimisation 4 Assumption 3 (Op 4 As 3). Although we simulate all payoffs using all models of optimisation, we

only show the best payoff in whole year data. The results are similar to those from previous experiments, showing that Op 4 As 3 outperforms others.

Figure 21: Payoff Comparisons in January and October 2018

Figure 21 shows that Optimisation 4 outperforms Optimisations 1, 2 and 3. In terms of market settlement, Op 4 As 3 also appears to outperform other assumptions. These findings are consistent with our previous experiments.

In Table 10 and 11, we only show the best daily and monthly payoff of our 2018 CE data based on our optimisation using Op 4 As 3. All payoff optimisations in these months are for cost minimisation. Further, we will compare these results using our baseline data to show the battery and optimisation performances.

Table 10. January-June Optimum Payoff (in £)

Day	Jan	Feb	Mar	Apr	May	Jun
$\mathbf{1}$	-232.4874	-536.8247	-184.2367	-598.8262	-126.0972	-759.8190
2	-379.0370	-623.7981	-552.6853	-321.8634	-156.3902	-530.7305
3	-249.9371	-862.4193	-652.7072	-245.0325	-518.9199	-386.1616
4	-418.3558	-470.3067	-497.2674	-335.4496	-460.5861	-439.6240
5	-551.5389	-519.4757	-547.5723	-436.9692	-266.3085	-536.1579
6	-717.6749	-842.9887	-741.6213	-261.7031	-310.3348	-363.1608
$\overline{7}$	-239.2802	-916.5589	-701.3691	-332.6760	-460.1435	-612.4162
8	-631.1237	-836.9559	-281.1479	-479.4669	-564.0242	-605.5900
9	-867.9360	-533.6637	-715.1502	-671.0404	-458.8963	-445.1457
10	-867.9360	-533.6637	-715.1502	-671.0404	-458.8963	-445.1457
$11\,$	$-1,025.9305$	-187.3776	-496.5037	-771.9320	-467.6831	-357.2778
12	$-1,025.0653$	-548.3539	-345.2424	-768.1832	-355.6013	-487.9730
13	-798.6555	-332.8183	-577.2173	-684.4698	-550.8374	-555.1437
14	-618.4573	-334.5628	-467.6525	-564.4787	-335.9091	-381.9986
15	-280.3849	-548.6184	-565.7572	-502.0898	-364.1395	-511.9805
16	-234.2759	-742.7995	-685.6163	-548.8974	-232.4866	-283.7769
17	-264.0836	-754.0706	-286.9386	-476.3663	-172.4642	-225.0012
18	-452.1217	-639.0032	-224.6933	-490.6809	-413.2314	-272.1420
19	-576.5009	-881.1024	-431.4165	-450.7009	-553.8752	-595.7777
20	-774.6006	-905.9870	-399.0229	-534.9004	-288.5705	-350.6321
21	-631.5215	-673.8582	-718.9543	-432.2486	-352.6036	-171.2446
22	-675.5079	-386.0259	-659.4200	-238.3721	-507.2372	-242.3284
23	-438.8415	-304.1215	-557.4379	-303.0341	-473.8619	-410.1663
24	-210.9351	-115.7546	-558.0204	-317.6296	-476.9516	-370.1777
25	-676.6970	-175.5068	-539.1656	-172.7604	-543.5732	-506.1836
26	-900.6179	-454.5713	-731.1405	-234.0938	-276.1607	-361.3206
27	-485.4011	-580.6233	-702.1468	-546.9534	-320.1779	-297.4112
28	-235.8993	-282.0825	-708.2380	-416.0655	-408.1762	-230.5177
29	-317.9832		-574.1519	-500.7343	-526.2339	-198.0002
30	-822.1915		-515.9331	-126.7750	-555.6413	-214.3314
31	-283.4830		-528.4589		-630.8123	
Monthly	$-16,884.46$	-15,523.89	$-16,862.04$	$-13,435.43$	$-12,586.83$	$-12,147.34$

Day	Jul	Aug	Sep	Oct	Nov	Dec
$\mathbf 1$	-209.2878	-477.5489	-425.3192	-239.9690	-279.3050	-142.7024
$\overline{2}$	-343.2903	-453.1893	-314.7645	-255.3178	-541.1100	-47.6463
3	-488.2038	-444.4958	-656.6117	-473.9375	-537.3100	-263.0684
$\pmb{4}$	-727.7221	-275.8081	-573.4846	-620.1566	-491.4084	-844.5343
5	-742.5104	-289.7699	-655.5702	-518.8627	-681.6634	-581.0806
6	-757.4415	-427.5654	-631.7787	-315.8783	-442.4137	-435.6656
$\overline{7}$	-562.6563	-502.8043	-296.6068	-276.7489	-175.2507	-77.6997
8	-474.3867	-317.2924	-332.6625	-556.9687	-521.5664	68.9981
9	-637.8168	-387.3956	-306.0711	-589.3307	-442.8509	-61.0971
10	-637.8168	-387.3956	-306.0711	-573.0107	-442.8509	-61.0971
11	-631.3745	-283.3124	-35.8094	-181.6388	-145.1997	-927.3786
12	-658.4770	-233.8063	-642.7658	-148.4462	-613.7499	-843.5592
13	-675.3581	-494.1644	-693.7989	-63.0911	-313.4444	-484.2156
14	-515.7027	-517.3962	-484.9290	-234.6099	-565.4874	-872.5219
15	-496.9397	-355.7353	-408.7718	-542.5387	-746.1415	-438.1259
16	-690.7840	-328.1743	-341.8422	-684.6531	-863.7318	-674.7425
17	-497.6150	-483.8543	-455.3035	-679.6544	-316.8463	-505.5186
18	-703.9739	-320.5437	-53.6010	-590.4036	-193.6693	-311.2126
19	-690.9076	-157.0998	-202.4271	-663.6405	-198.4937	-370.9634
20	-760.7553	-756.6243	-176.3760	-621.4347	-330.1308	-294.2415
21	-518.7647	-627.6480	101.9866	-565.7958	-792.5695	-11.6798
22	-527.9187	-562.0177	-418.1137	-473.3147	-860.7646	-153.9995
23	-669.9664	-523.0619	-426.0521	-232.0586	-802.4268	-442.5363
24	-717.9564	-197.4220	-444.8270	-632.2466	-797.8229	-713.4803
25	-672.7481	-210.0258	-609.2684	-823.1847	-714.1926	-648.9801
26	-686.1961	-179.5620	-509.3559	-535.7051	-900.8271	-752.4543
27	-642.8893	-220.0823	-537.5027	-447.4521	-755.7320	-843.5757
28	-362.6993	-653.3324	-372.1464	-88.2675	-210.1239	-852.3117
29	-255.4039	-651.6366	-444.4470	-436.3583	-174.1430	-394.3005
30	-495.2214	-524.8283	-429.3243	-379.1050	-365.6737	-602.7067
31	-596.8399	-584.5835		-556.1572		-691.4472
Monthly	$-18,049.62$	$-12,828.18$	$-12,083.62$	$-13,999.94$	$-15,216.90$	$-14,275.55$

Table 11. July-December Optimum Payoff (in £)

We will compare some of the results in Table 10 and Table 11 against those retrieved using the same optimisation, but without battery. The comparison can indicate the battery impact in our optimisation.

Figure 22: Impact of Battery Use in January and July 2018

As seen in Figure 22, our optimisation becomes more effective. In January, where there is only 20.06kWh stored, our batteries contribute £0.65. Using our calculation, the battery owner gets £0.20. In July, where there is 2156.35 kWh stored, our batteries contribute £74.36. Using our calculation, the battery owner gets £21.56. These suggest that all members get benefits from the use of battery in our CE.

4.4 Community Energy Internal Selling Price, Internal Buying Price and Diff

Although calculation on ISP, IBP and Diff can be done on a daily, weekly or monthly basis, the end customer generally pays the electricity on a monthly basis. From customer perspectives, daily electricity price fluctuation could mean adversity when it does not create economic benefit.

Figure 23: ISP, IBP and Diff in January 2018

Figure 24: ISP, IBP and Diff in April 2018

As seen in Figure 23 and Figure 24, the daily equilibrium price difference between ISP and IBP in January are mostly below £0.002/kWh, except on the 10th which almost reaches £0.006/kWh. The prices are slightly higher in April, mostly being under £0.005, except on the 10th which exceeds £0.025/kWh. This fluctuation may occur because of uncertainty of load and generation. As previously explained, our CE assumes that there are only micro renewable energy generators for the generators which highly depend on the weather and that our loads are unshifted and uninterruptable.

Figure 25: ISP, IBP and Diff in 2018

As we are only required to sum the total weekly payoffs and loads as well as generations before quantifying the equilibrium prices, there will not be any effect if we propose weekly or monthlybased equilibrium prices, although our transactions are on an hourly basis. As seen in Figure 25, Figure 23 and Figure 24, we can clearly compare our daily, weekly and monthly basis equilibrium prices. Rather than using daily-based prices, which require more complex calculation and are less comfortable to the CE members, we try to offer weekly or monthly equilibrium prices.

Figure 26: Payoff Comparison with Baseline Data

The results enable us to compare our optimisation using our baseline data. Rather than using fixed price in this baseline data, we use peak/off-peak tariff price, which is better from fixed tariff. As seen in Figure 26, our optimisation has already outperformed the baseline data by 18.37%. In terms of money, use of our optimisation suggests that CE can save (reduce cost by) £39,121.57 in a year.

It is essential to state that our CEMS optimisation gives positive outcome to all CE members, such as electricity suppliers (micro renewable energy generators owners) and customers. In terms of electricity buying prices and supply, the benefits are:

Table 12: Benefit for CE Members in term of Electricity Price

Chapter 5 Analysis and Discussion

In this chapter, we analyse our results from Chapter 3 and Chapter 4 and discuss some findings before making conclusions.

As mentioned in Chapter 2 and Section 3.1, our optimisation can be classified as hierarchical model optimisation. It consists of internal and external levels, run step-by-step.

In internal level:

- 1. Collecting load and generation data as well as battery status.
- 2. Planning internal planning settlement because of the gap between load and generation data. The planning consists of how much energy is charged or discharged from the battery and also considers the potential energy surplus or deficits in advance.
- 3. All planning must follow the battery and network constraints.
- 4. Remaining electricity imbalance will be settled in external level.

In external level:

- 1. The optimisation starts with market and is followed by retailer settlements.
- 2. Consists of market and retailer settlements.
- 3. In market settlement, it depends on our strategy and market response regarding our ask/bid. We made some assumptions for market response.
- 4. All remaining imbalance caused by immediate load and generation fluctuations will be settled by retailers using fixed or peak/off-peak tariff and FIT or export tariff.

As seen from the optimisation formulas that refer to the type of CEMS in Section [3.2,](#page-57-0) basically the optimisation is gradually done and monotonic. Consequently, when we use CEMS type 3, we already hired CEMS type 2. When we use CEMS type 2, we already did CEMS type 1. The best payoff can be reached using CEMS type 3.

- 1. $(Surplus(t) \times ET) (Deficit(t) \times RP) \leq ((Surplus(t) Ch(t)) \times ET) ((Deficit(t) 0.9$ $Ch(t))xRP$
- 2. $((Surplus(t) Ch(t)) \times ET) ((Deficit(t) 0.9 Ch(t)) \times RP) \le ((Surplus(t) Ch(t)) \times CP)$ $(maxket\; coef) \times MSP$ + $((Surplus(t) - Ch(t)) \times (1 - market\; coef) \times ET)$ - $((Deficit(t) - 0.9 Ch(t)) \times (market coeff) \times MBP) - ((Deficit(t) - 0.9 Ch(t)) \times (1$ market coef) \times RP), market coef \leq 1; ET \lt MSP; RP $>$ MBP.

As mentioned in Subsection [3.3.1,](#page-60-0) Optimisations 1 (C2STF), 2 (C2POTF) and 3 (C2POTD) can be done by using CEMS type 2. These type of optimisation does not include market settlement – it is classified as internal level optimisation. CEMS type 3 uses both internal and external level optimisation which include market settlement, named as Optimisation 4 (C3MPD). In this optimisation, we use 3 market responses as our assumption in response to our ask/bid. All market bid or ask, and response guarantee better payoff relative to Optimisations 1 (C2STF), 2 (C2POTF) and 3 (C2POTD)

Three types of CE daily profile which depict the possible CE status at a time have been presented as our experiment data – they are deficit, surplus and balanced CE, as seen in Subsection 3.3.1. In this experiment, we use a large number of batteries to minimise battery limitation in terms of charging/discharging and energy stored.

Results from our experiment suggest that better payoff can be obtained by using peak/off-peak tariff rather than fixed tariff. In Subsection 3.3.3.1, we mention that, as long as buying transaction during off-peak time is more than 4/3 in peak time, the result will be better regardless of the daily profile (deficit or balanced). The key is to minimise buying electricity in the peak time and peak/ off-peak buying comparison rate. We formulate the buying ratio comparison using the equation below:

$$
\left(OffPeak\ Buying * \frac{E0.11}{kWh}\right) + \left(Peak\ Buying * \frac{E0.18}{kWh}\right)
$$

$$
\leq ((Offpeak\ Buying + Peak\ Buying) * E0.14/kWh)
$$

When compared to Optimisation 1 (C2STF), Optimisation 2 (C2POTF) could not yield better results in surplus profile. This is because the export tariff remains the same at all times and using battery means some energy losses, as suggested in Table 4. Overall, the Optimisation 3 results outperform those of Optimisations 1 (C2STF) and 2 (C2POTF). This indicates that using dynamic 24 hours in advance is better than fixed daily-based optimisation as the optimisations show monotonic increase in deficit profile.

Simulation showed in Subsection 3.3.3.1 suggests that each type of CE has a different best strategy to get the optimum payoff. In terms of deficits, using the third assumption generates optimum payoff, followed by the second assumption. In terms of surplus, the second assumption results in optimum payoff, followed by the first assumption. In balanced profile, the third assumption is better than the second assumption.

Battery can improve the payoff results in all types of profiles, as shown in Figure 11, Figure 12, Figure 13, and Figure 14, the most significant result being *Exp 3B*. In this experiment, battery is used more often, as suggested by a nearly balanced profile where fluctuations occur. This deficit

and surplus can be settled by battery charge and discharge. The impact of using battery appears to be highly significant (Figure 14) as we minimised the battery limitation in the experiment.

Figure 27: Pareto Optimality in ISP and IBP in Equilibrium Prices Candidate

An equilibrium price can only be obtained when CE is in a balanced electricity profile which produces optimum payoff. It is also in such a way that no user can achieve a better payoff without making another user worse off (so called Pareto-optimal), as shown in Figure 27.

For CE members, the most important issue of EMS is economic benefits. The higher ISP and lower IBP are presented as the main evidence. In view of these prices, we choose uniform ISP for all electricity generation and uniform IBP for all electricity load. In balanced profile, the best price for ISP and IBP is at mid-price (equilibrium price). The price will be higher when loads are bigger than generation, and vice versa. This type of (equilibrium) price is in accordance with economics law.

Figure 28: Binary Search Example Model of Finding ISP or IBP

Rather than checking all possibilities in every ISP and IBP nodes or using binary search and the optimisation formula, we try to find the equilibrium price candidates. These ISP or IBP candidates should satisfy our constraints. We find ISP and IBP which meet the criteria to become equilibrium

price. The best ISP and IBP can be found using our method until minimum difference; however, our results prove that, at the fifth iteration, the significant ISP and IBP are already found. Figure 15 and Figure 27 show that from the first and second until the fifth iteration in finding ISP and IBP, the results are monotonically convergent.

According to Figure 18, no significant impact was shown between Optimisations 3 (C2POTD) and 4 (C3MPD). This is because, in the nearly balanced profile, there are not many markets and retailer settlements since all surpluses and deficits can be handled by utilising battery.

Our CE data showed that all monthly profiles are deficits. According to our experiment, the best option for optimising CE is by using Optimisation 4 (C3MPD) Assumption 3. Although no surplus is detected on a monthly basis, many surplus profiles are observed on a daily basis. Optimisation can be effectively run by utilising battery if fluctuations exist between surplus and deficit in the CE.

Parallel with our experiments, the battery gives positive impact on payoff optimisation. With battery limitation, it could provide £74.36 in July 2018 when we stored 2,156.35 kWh, equivalent to £0.0345/kWh. This can support CE members since, eventually, the battery owners only get a fee from CE £0.01/kWh.

Figure 25 suggests that by using the fifth iteration in 2018, our CEMS can achieve equilibrium prices, as follows:

 $0.0991 \leq ISP \leq 0.1078, 0.0994 \leq IBP \leq 0.1080, 0.0001 \leq Diff \leq 0.0011$

The ISP, IBP and Diff are somewhat significant for 3,124,655.87kWh load and 1,453,429.71kWh generation in total with a total payoff of -£173,893.79.

Using data from Table 12, should CE members use fixed tariff and FIT, the CE gets:

- *Customers get* = $\frac{10.0362}{kWh} \times 3,124,655.87$ kWh = £11,312.5425
- $mREGs$ owners $get = E \frac{0.0633}{kWh} \times 1,453,429.71$ $kWh = \text{\textsterling}92,002.1006$

According to our simulation results, our CEMS and optimisations can create significant benefits to all CE members. In term of CE aggregator or management profit, we can use many kinds of profit sharing. We do not discuss in this chapter, since we assume that CE aggregator or management is also CE owner which is Battery owner as well.

Chapter 6 Conclusions and Further Work

This chapter sums up our work and briefly discusses suggested future work following this research, specifically the need for expanding the optimisation by considering shiftable and controllable demands. Dynamic battery and micro renewable electricity generator setting are interesting to address when new groups of battery and micro renewable electricity generator owners wish to join our CE, while also opening the possibility for plug-in electric vehicle owners to join as customer, supplier or battery owner.

6.1 Conclusions

The work presented in this thesis addressed the designing of an agent as a part of CEMS to optimise the benefit of local electricity generation. While maintaining electricity balance, the agent has performed some optimisations in order to optimise benefits.

In the first part of this thesis, the essence of smart grid and microgrid were discussed and followed by several models of EMS, which included virtual power plan, demand side management, demand response and their relation between our optimisation model for CEMS with the literature. electricity trading and the electricity market within the community are also discussed, specifically about the double auction and continuous double auction market model, including several projects that have been proposed in the literature.

The next chapter explained our CE model, which includes generation and load models, CE profile and battery models as well as retailer and market settlement models. This chapter also explained our CE optimisations in relation to the types of CEMS. Our optimisation can be classified as hierarchical model optimisation since there are internal and external level optimisations. The optimisations are monotonic since (local electricity) market settlement create best payoff followed by retailer only settlement. For each type of CEMS, they have different best strategies in terms of achieving optimum payoff. Lastly, the use of battery has a highly significant positive impact to create optimum payoff, particularly when we minimise the battery limitation. For CE members' settlements, ISP and IBP are founded as equilibrium prices, which guarantee satisfaction of all members. Using a binary search algorithm, we collected ISP and IBP candidates which are monotonically convergent. Acceptable ISP and IBP can be found within the fifth iteration.

In Chapter 4, our CE setting and profile are described. The data pattern is collected from [www.elia.be.](http://www.elia.be/) Extended simulation using 2018 data to calculate the optimum payoffs (both daily

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and monthly) has been carried out, and equilibrium price for ISP and IBP was found using the same method as in the previous chapter.

Finally, we discussed and analysed our results. The characteristics of our CEMS and optimisations have been explained in detail followed by illustrations and some mathematical expressions. The results and performances of our optimisations for every type of CEMS were also explained and compared. Finding equilibrium prices for ISP and IBP was also explained in detail and showed a very significant positive difference compared with electricity trading and RP.

We have highlighted some conclusions regarding the benefits of using our CEMS optimisation for all CE members. With particular regard to cost minimisation or profit maximisation, the conclusions are:

- 1. Our models, optimisations and market response assumptions are capable of achieving optimum profits for CE, which can be shown using the optimum payoff.
- 2. Local electricity market and battery give positive impact to all CE members, despite several battery limitations.
- 3. Our CEMS ensure positive outcomes as well as offer ease for all members in terms of financial settlement. While our optimisation is running every day, price settlement to all CE members can be done on a monthly basis. It, therefore, affords an easier approach to all CE members since they do not have to deal with financial settlement on an hourly or daily basis as required by auction approaches.
- 4. ISP and IBP appear to have a very significant impact relative to electricity trading and RP following results which approximate the competitive equilibrium price.

6.2 Further Work

Expanding data into several places which have different loads and generation patterns will enrich our experiment data. Parallel with the massive penetration of IoT and manageable household electricity equipment, considering the shiftable and controllable demands will give significant impact, because CE can manage load before making settlement.

Adding more dynamic battery and micro renewable electricity generator setting are also interesting to address when a new group of battery and micro renewable electricity generator owners want to join our CE. It will also help to create more balanced CE profiles and, thus, provide more benefits to CE members by reducing market and retailer settlement.

It is also interesting to exercise the possibility for plug-in electric vehicle owners to join as customer, supplier or battery owner. With these capabilities, a plug-in electric vehicle owner will play a very significant role in our CE.

Lastly, in terms of detailed optimum battery size and limitation which can create maximum payoff, we need to run the simulation using different battery profiles. This result is important to address the possibility for investing in battery in the current CE.

Lastly, implementing into MAS for our CE members after finding optimum payoff, in term of profit sharing, which includes battery owner will be very interesting. We can compare the price for customers, renewable electricity generators owners and battery owner with our current result in order to see the difference.

Appendix A Experiments and Simulation

This appendix consists of: (1) CE Data Experiments (includes 7-day Generation and Load data), (2) Simulation on Experiment Data Using Optimisation 4 Which Generate Optimum Payoff, and (3) ISP, IBP and Diff for Experiments 1 (surplus) and 2 (deficit).

Tables in this appendix relate to Experiments 1, 2 and 3 which have been discussed in Sectio[n 3.3.](#page-60-1)

A.1 Community Energy Data Experiments

hh/dd	$\mathbf{1}$	2	3	4	5	6	7
1	3.07	3.08	13.89	1.06	1.44	2.99	1.06
2	5.64	5.48	14.64	1.87	2.41	2.62	1.04
3	7.91	7.64	15.66	3.66	3.42	1.15	1.89
4	10.13	9.67	15.75	1.96	3.79	1.02	1.81
5	12.06	12.00	10.47	6.09	4.21	0.98	1.84
6	14.04	14.91	7.97	4.43	5.84	0.94	5.16
7	16.05	16.85	11.11	4.62	9.69	1.96	11.84
8	16.92	15.53	11.44	6.62	12.99	9.32	15.18
9	15.01	13.83	14.16	4.19	12.52	12.31	15.15
10	17.25	12.13	12.29	8.08	11.21	19.24	21.78
11	12.69	15.11	6.09	2.25	9.13	5.03	32.19
12	13.90	17.48	18.00	6.88	7.17	15.89	38.69
13	8.03	20.09	29.55	6.60	4.38	37.48	35.98
14	5.01	17.99	26.86	14.01	3.43	39.48	25.80
15	6.24	13.32	18.93	14.15	5.52	32.59	5.32
16	9.04	5.54	11.70	22.80	10.37	18.80	5.62
17	12.11	7.36	10.19	14.45	9.00	15.03	12.77
18	17.90	9.21	3.85	13.12	17.90	7.60	1.88
19	18.58	10.24	2.22	7.36	6.89	2.00	2.24
20	17.08	11.71	2.42	4.20	1.92	3.67	2.21
21	14.28	14.73	2.38	2.21	1.99	2.41	2.23
22	10.57	10.33	2.05	1.93	1.95	1.64	1.87
23	7.06	8.18	2.17	0.92	1.91	1.14	1.50
24	3.45	9.57	2.49	0.34	1.76	0.22	0.29
Daily	274.01	281.97	266.27	153.82	150.84	235.51	245.35

Table 13. Generation Data *Exp 1D* (in kW)

hh/dd	1	2	3	4	5	6	7
1	-33.75	-33.90	-26.53	-22.36	-15.89	-32.87	-22.16
2	-33.82	-32.88	-26.83	-20.59	-14.49	-28.79	-21.81
3	-34.29	-33.10	-27.71	-21.93	-14.81	-24.13	-22.85
4	-35.46	-33.85	-27.00	-21.60	-13.25	-21.43	-21.96
5	-36.17	-36.00	-22.10	-26.38	-12.63	-20.65	-20.23
6	-37.44	-39.76	-21.25	-26.59	-15.57	-19.64	-22.35
7	-38.98	-40.92	-26.99	-27.73	-23.52	-21.56	-28.76
8	-38.08	-34.94	-24.14	-28.70	-29.23	-24.86	-27.83
9	-33.77	-31.12	-25.05	-25.16	-28.18	-20.52	-21.74
10	-35.95	-27.21	-28.43	-26.98	-25.88	-19.83	-21.13
11	-33.84	-25.19	-26.40	-24.73	-24.36	-20.29	-22.13
12	-41.71	-24.47	-25.20	-24.07	-21.52	-19.42	-26.60
13	-28.11	-22.22	-24.93	-23.10	-15.32	-20.44	-22.65
14	-21.72	-17.70	-22.60	-21.02	-14.87	-21.54	-20.93
15	-21.84	-18.87	-20.82	-20.05	-19.33	-19.01	-18.63
16	-27.12	-16.61	-22.34	-24.55	-31.12	-14.62	-16.87
17	-32.28	-19.62	-22.92	-26.49	-38.98	-18.30	-19.86
18	-43.48	-22.36	-23.10	-24.06	-43.48	-18.46	-20.65
19	-49.55	-24.86	-24.42	-25.75	-41.31	-22.02	-30.27
20	-51.24	-26.34	-26.62	-25.20	-40.40	-28.14	-33.86
21	-49.97	-31.09	-26.18	-24.26	-41.73	-26.54	-34.03
22	-45.78	-25.09	-22.56	-21.27	-41.02	-25.09	-33.07
23	-42.35	-21.81	-23.83	-19.33	-40.15	-23.93	-31.56
24	-37.93	-23.24	-27.36	-17.48	-36.86	-21.73	-29.47
Daily	-884.62	-663.17	-595.32	-569.39	-643.89	-533.79	-591.42

Table 14. Load Data *Exp 1D* (in kW)

Table 15. Generation Data *Exp 2S* (in kW)

hh/dd	1	$\overline{2}$	3	4	5	6	7
1	64.42	64.72	26.53	44.72	30.34	62.74	44.32
2	59.18	57.53	25.61	39.32	25.36	54.96	43.63
3	55.38	53.47	25.30	38.38	23.93	48.25	44.02
4	53.19	50.77	23.63	41.24	19.87	42.86	42.31
5	50.64	50.40	24.43	42.62	17.68	41.30	38.61
6	49.13	52.19	27.90	46.53	20.43	39.29	36.11
7	48.15	50.55	33.34	48.53	29.06	41.17	35.53
8	44.43	40.77	26.69	46.37	34.10	32.62	26.56
9	39.40	36.31	22.87	44.03	32.88	17.23	13.84
10	39.28	31.67	33.90	39.68	30.81	1.24	-1.38
11	44.41	21.16	42.64	47.21	31.97	32.03	-21.13
12	58.40	14.68	15.12	36.10	30.13	7.41	-25.39
13	42.17	4.49	-9.70	34.65	22.99	-35.78	-27.98
14	35.09	-0.62	-8.95	14.71	24.01	-37.69	-10.22
15	32.75	11.65	3.97	12.38	28.99	-28.52	27.95
16	37.97	23.26	22.34	3.68	43.57	-8.77	23.61
17	42.37	25.76	26.74	25.29	62.97	6.86	14.90
18	53.71	27.62	40.43	22.97	53.70	22.81	39.43
19	65.03	30.71	46.61	38.62	72.30	42.05	58.87
20	71.73	30.73	50.82	44.11	80.80	51.39	66.45
21	74.96	34.36	49.98	46.31	83.46	50.66	66.78
22	73.96	31.00	43.07	40.61	82.04	49.24	65.52
23	74.10	28.62	45.50	38.66	80.30	47.86	63.13
24	72.42	28.71	52.23	36.00	73.72	45.18	61.27
Daily	1282.28	800.53	691.00	872.71	1035.40	626.39	726.74

hh/dd	1	$\overline{2}$	3	4	5	6	7
1	-33.75	-33.90	-13.89	-23.42	-15.89	-32.87	-23.22
2	-31.00	-30.14	-13.42	-20.59	-13.28	-28.79	-22.85
3	-29.01	-28.01	-13.25	-20.10	-12.53	-25.27	-23.06
4	-27.86	-26.60	-12.38	-21.60	-10.41	-22.45	-22.16
5	-26.53	-26.40	-12.80	-22.33	-9.26	-21.63	-20.23
6	-25.74	-27.34	-14.61	-24.37	-10.70	-20.58	-18.92
7	-25.22	-26.48	-17.47	-25.42	-15.22	-21.56	-18.61
8	-23.27	-21.35	-13.98	-24.29	-17.86	-17.09	-13.91
9	-20.64	-19.02	-11.98	-23.06	-17.22	-9.03	-7.25
10	-20.57	-16.59	-17.76	-20.78	-16.14	-0.65	0.72
11	-23.26	-11.08	-22.34	-24.73	-16.75	-16.78	11.07
12	-30.59	-7.69	-7.92	-18.91	-15.78	-3.88	13.30
13	-22.09	-2.35	5.08	-18.15	-12.04	18.74	14.66
14	-18.38	0.32	4.69	-7.71	-12.58	19.74	5.36
15	-17.16	-6.10	-2.08	-6.49	-15.19	14.94	-14.64
16	-19.89	-12.18	-11.70	-1.93	-22.82	4.60	-12.37
17	-22.19	-13.49	-14.01	-13.25	-32.99	-3.59	-7.80
18	-28.13	-14.47	-21.18	-12.03	-28.13	-11.95	-20.65
19	-34.06	-16.09	-24.42	-20.23	-37.87	-22.02	-30.83
20	-37.57	-16.10	-26.62	-23.10	-42.33	-26.92	-34.81
21	-39.26	-18.00	-26.18	-24.26	-43.72	-26.54	-34.98
22	-38.74	-16.24	-22.56	-21.27	-42.97	-25.79	-34.32
23	-38.82	-14.99	-23.83	-20.25	-42.06	-25.07	-33.07
24	-37.93	-15.04	-27.36	-18.86	-38.61	-23.66	-32.09
Daily	-671.67	-419.32	-361.95	-457.13	-542.35	-328.11	-380.67

Table 16. Load Data *Exp 2S* (in kW)

Table 17. Generation Data *Exp 3B* (in kW)

hh/dd	1	$\overline{2}$	3	4	5	6	7
1	27.61	27.74	24.00	18.10	13.00	26.89	17.94
2	28.18	27.40	24.39	16.85	12.07	23.55	17.66
3	29.01	28.01	25.30	18.28	12.53	19.53	18.66
4	27.86	26.60	23.63	15.71	10.41	15.31	15.92
5	26.53	26.40	17.45	18.27	9.26	12.78	12.87
6	25.74	27.34	14.61	15.51	10.70	10.29	13.76
7	41.27	43.33	28.58	30.04	24.91	23.52	30.45
8	44.43	40.77	27.96	35.33	34.10	29.52	31.62
9	43.16	39.76	30.49	35.64	36.01	24.62	25.04
10	49.04	37.76	39.73	40.21	36.15	20.24	21.59
11	52.87	34.26	44.67	44.97	38.06	34.01	31.19
12	69.52	31.46	32.40	41.26	35.87	22.95	38.69
13	48.20	24.36	29.55	39.60	26.27	37.48	35.98
14	38.43	17.99	26.86	28.02	26.30	39.48	25.80
15	34.31	23.31	22.34	24.76	30.37	29.87	29.28
16	37.97	23.26	28.72	25.60	43.57	17.13	23.61
17	40.35	24.53	28.01	31.31	50.98	19.60	22.70
18	48.59	24.99	26.95	26.25	48.59	20.64	24.41
19	43.35	21.94	19.98	22.07	34.43	18.02	24.67
20	34.16	19.03	14.52	14.70	21.16	15.91	18.04
21	32.12	22.91	14.28	13.23	21.86	14.48	18.13
22	31.70	19.19	14.36	13.54	25.39	15.71	20.59
23	31.76	17.72	17.33	13.81	28.68	17.09	22.55
24	31.04	20.51	22.39	14.06	29.84	17.43	23.63
Daily	917.20	650.55	598.50	597.10	660.51	526.05	564.75

hh/dd	1	$\overline{2}$	3	4	5	6	7
1	-33.75	-33.90	-26.53	-22.36	-15.89	-32.87	-22.16
2	-33.82	-32.88	-26.83	-20.59	-14.49	-28.79	-21.81
3	-34.29	-33.10	-27.71	-21.93	-14.81	-24.13	-22.85
4	-35.46	-33.85	-27.00	-21.60	-13.25	-21.43	-21.96
5	-36.17	-36.00	-22.10	-26.38	-12.63	-20.65	-20.23
6	-37.44	-39.76	-21.25	-26.59	-15.57	-19.64	-22.35
7	-38.98	-40.92	-26.99	-27.73	-23.52	-21.56	-28.76
8	-38.08	-34.94	-24.14	-28.70	-29.23	-24.86	-27.83
9	-33.77	-31.12	-25.05	-25.16	-28.18	-20.52	-21.74
10	-35.95	-27.21	-28.43	-26.98	-25.88	-19.83	-21.13
11	-33.84	-25.19	-26.40	-24.73	-24.36	-20.29	-22.13
12	-41.71	-24.47	-25.20	-24.07	-21.52	-19.42	-26.60
13	-28.11	-22.22	-24.93	-23.10	-15.32	-20.44	-22.65
14	-21.72	-17.70	-22.60	-21.02	-14.87	-21.54	-20.93
15	-21.84	-18.87	-20.82	-20.05	-19.33	-19.01	-18.63
16	-27.12	-16.61	-22.34	-24.55	-31.12	-14.62	-16.87
17	-32.28	-19.62	-22.92	-26.49	-38.98	-18.30	-19.86
18	-43.48	-22.36	-23.10	-24.06	-43.48	-18.46	-20.65
19	-49.55	-24.86	-24.42	-25.75	-41.31	-22.02	-30.27
20	-51.24	-26.34	-26.62	-25.20	-40.40	-28.14	-33.86
21	-49.97	-31.09	-26.18	-24.26	-41.73	-26.54	-34.03
22	-45.78	-25.09	-22.56	-21.27	-41.02	-25.09	-33.07
23	-42.35	-21.81	-23.83	-19.33	-40.15	-23.93	-31.56
24	-37.93	-23.24	-27.36	-17.48	-36.86	-21.73	-29.47
Daily	-884.62	-663.17	-595.32	-569.39	-643.89	-533.79	-591.42

Table 18. Load Data *Exp 3B* (in kW)

A.2 Simulation on Experiment Data Using Optimisation 4 Which Generates Optimum Payoff

To understand the data from **[Table 20](#page-100-0)** to **[Table 31](#page-121-0)**, here are the explanation of each column and it's unit:

Table 20. Op 4 As 3 Result from *Exp 1D* for Days 1 and 2

D		24h Pot S $24h$ Pot D	Ch	DisCh	BS	Offer	Ask	SellM	BuyM	TransM	SellG	BuyG	TransG	Payoff
1		0.0000 -610.6095	0.0000	0.0000	200.0000	0.0000	30.6780	0.0000	12.2712	-1.1044	0.0000	18.4068	-2.0248	-3.1292
		0.0000 -610.7486	0.0000	0.0000	200.0000	0.0000	28.1797	0.0000	11.2719	-1.0145	0.0000	16.9078	-1.8599	-2.8743
		0.0000 -609.9662	0.0000	0.0000	200.0000	0.0000	26.3737	0.0000	10.5495	-0.9495	0.0000	15.8242	-1.7407	-2.6901
		0.0000 -609.0567	0.0000	0.0000	200.0000	0.0000	25.3287	0.0000	10.1315	-0.9118	0.0000	15.1972	-1.6717	-2.5835
		$0.0000 - 607.9063$	0.0000	0.0000	200.0000	0.0000	24.1163	0.0000	9.6465	-0.8682	0.0000	14.4698	-1.5917	-2.4599
		0.0000 -607.7922	0.0000	0.0000	200.0000	0.0000	23.3975	0.0000	9.3590	-0.8423	0.0000	14.0385	-1.5442	-2.3865
	0.0000	-609.2472	0.0000	0.0000	200.0000	0.0000	22.9291	0.0000	9.1716	-0.8254	0.0000	13.7574	-1.5133	-2.3388
		$0.0000 - 610.3900$	0.0000	0.0000	200.0000	0.0000	21.1551	0.0000	8.4620	-0.7616	0.0000	12.6931	-1.3962	-2.1578
	0.0000	-608.6475	0.0000	0.0000	200.0000	0.0000	18.7631	0.0000	7.5052	-0.6755	0.0000	11.2578	-1.2384	-1.9138
		0.0000 -607.1730	0.0000	0.0000	200.0000	0.0000	18.7039	0.0000	7.4816	-0.6733	0.0000	11.2224	-1.2345	-1.9078
	0.0000	-603.5492	0.0000	0.0000	200.0000	0.0000	21.1481	0.0000	8.4592	-0.7613	0.0000	12.6889	-1.3958	-2.1571
		0.0000 -592.4777	0.0000	0.0000	200.0000	0.0000	27.8075	0.0000	11.1230	-1.0011	0.0000	16.6845	-1.8353	-2.8364
		0.0000 - 571.6607	0.0000	0.0000	200.0000	0.0000	20.0818	0.0000	8.0327	-0.7229	0.0000	12.0491	-1.3254	-2.0483
		0.0000 -553.7158	0.0000	0.0000	200.0000	0.0000	16.7078	0.0000	6.6831	-0.6015	0.0000	10.0247	-1.1027	-1.7042
		0.2935 -537.0080	0.0000	0.0000	200.0000	0.0000	15.5973	0.0000	6.2389	-0.5615	0.0000	9.3584	-1.0294	-1.5909
		$0.2935 - 526.9605$	0.0000	0.0000	200.0000	0.0000	18.0805	0.0000	7.2322	-0.6509	0.0000	10.8483	-1.1933	-1.8442
		0.2935 - 519.9552	0.0000	0.2600	199.7400	0.0000	19.9159	0.0000	7.9664	-1.1153	0.0000	11.9496	-2.1509	-3.2662
		$0.2935 - 512.0440$	0.0000	0.0000	199.7400	0.0000	25.5758	0.0000	10.2303	-1.4322	0.0000	15.3455	-2.7622	-4.1944
		$0.2935 - 499.6183$	0.0000	0.0000	199.7400	0.0000	30.9672	0.0000	12.3869	-1.7342	0.0000	18.5803	-3.3445	-5.0786
		$0.2935 - 483.2768$	0.0000	0.0000	199.7400	0.0000	34.1575	0.0000	13.6630	-1.9128	0.0000	20.4945	-3.6890	-5.6018
		$0.2935 - 463.7549$	0.0000	0.0000	199.7400	0.0000	35.6936	0.0000	14.2774	-1.2850	0.0000	21.4162	-2.3558	-3.6407
		$0.2935 - 444.4248$	0.0000	0.0000	199.7400	0.0000	35.2192	0.0000	14.0877	-1.2679	0.0000	21.1315	-2.3245	-3.5924
		$0.2935 - 423.9660$	0.0000	0.0000	199.7400	0.0000	35.2878	0.0000	14.1151	-1.2704	0.0000	21.1727	-2.3290	-3.5994
		$0.2935 - 402.3085$	0.0000	0.0000	199.7400	0.0000	34.4844	0.0000	13.7937	-1.2414	0.0000	20.6906	-2.2760	-3.5174

Table 21. Op 4 As 3 Result from *Exp 1D* for Days 3 and 4

D		24h Pot S 24h Pot D	Ch	DisCh	BS	Offer	Ask	SellM	BuyM	TransM	SellG	BuyG	TransG	Payoff
3		8.8812 - 337.9272	0.0000	0.0000	192.0111	0.0000	12.6318	0.0000	5.0527	-0.4547	0.0000	7.5791	-0.8337	-1.2884
		8.8812 - 346.5883	0.0000	0.0000	192.0111	0.0000	12.1967	0.0000	4.8787	-0.4391	0.0000	7.3180	-0.8050	-1.2441
		8.8812 - 353.1136	0.0000	0.0000	192.0111	0.0000	12.0487	0.0000	4.8195	-0.4338	0.0000	7.2292	-0.7952	-1.2290
		8.8812 - 359.3419	0.0000	0.0000	192.0111	0.0000	11.2502	0.0000	4.5001	-0.4050	0.0000	6.7501	-0.7425	-1.1475
		8.8812 - 367.7297	0.0000	0.0000	192.0111	0.0000	11.6328	0.0000	4.6531	-0.4188	0.0000	6.9797	-0.7678	-1.1865
		8.8812 - 376.3927	0.0000	0.0000	192.0111	0.0000	13.2843	0.0000	5.3137	-0.4782	0.0000	7.9706	-0.8768	-1.3550
		8.8812 - 385.2633	0.0000	0.0000	192.0111	0.0000	15.8785	0.0000	6.3514	-0.5716	0.0000	9.5271	-1.0480	-1.6196
		8.8812 - 392.4956	0.0000	0.0000	192.0111	0.0000	12.7073	0.0000	5.0829	-0.4575	0.0000	7.6244	-0.8387	-1.2961
		8.8812 -401.8675	0.0000	0.0000	192.0111	0.0000	10.8905	0.0000	4.3562	-0.3921	0.0000	6.5343	-0.7188	-1.1108
		8.8812 -411.9442	0.0000	0.0000	192.0111	0.0000	16.1423	0.0000	6.4569	-0.5811	0.0000	9.6854	-1.0654	-1.6465
		8.8812 -414.6965	0.0000	0.0000	192.0111	0.0000	20.3058	0.0000	8.1223	-0.7310	0.0000	12.1835	-1.3402	-2.0712
		8.8812 - 416.8736	0.0000	0.0000	192.0111	0.0000	7.1999	0.0000	2.8799	-0.2592	0.0000	4.3199	-0.4752	-0.7344
		8.8812 -426.8651	4.6175	0.0000	196.1668	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		4.2637 - 443.3653	4.2637	0.0000	200.0042	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		0.0000 -450.3706	0.0000	0.0000	200.0042	0.0000	1.8928	0.0000	0.7571	-0.0681	0.0000	1.1357	-0.1249	-0.1931
		0.0000 -454.3739	0.0000	0.0000	200.0042	0.0000	10.6370	0.0000	4.2548	-0.3829	0.0000	6.3822	-0.7020	-1.0850
	0.0000	-445.4905	0.0000	0.0000	200.0042	0.0000	12.7329	0.0000	5.0932	-0.7130	0.0000	7.6397	-1.3752	-2.0882
		0.0000 -444.7990	0.0000	0.0000	200.0042	0.0000	19.2525	0.0000	7.7010	-1.0781	0.0000	11.5515	-2.0793	-3.1574
	0.0000	-436.4833	0.0000	0.0000	200.0042	0.0000	22.1966	0.0000	8.8786	-1.2430	0.0000	13.3180	-2.3972	-3.6402
		0.0000 -432.6775	0.0000	0.0000	200.0042	0.0000	24.1985	0.0000	9.6794	-1.3551	0.0000	14.5191	-2.6134	-3.9685
		$0.0000 - 429.4820$	0.0000	0.0000	200.0042	0.0000	23.8000	0.0000	9.5200	-0.8568	0.0000	14.2800	-1.5708	-2.4276
		0.0000 -427.7341	0.0000	0.0000	200.0042	0.0000	20.5087	0.0000	8.2035	-0.7383	0.0000	12.3052	-1.3536	-2.0919
		0.0000 -426.5643	0.0000	0.0000	200.0042	0.0000	21.6663	0.0000	8.6665	-0.7800	0.0000	12.9998	-1.4300	-2.2100
		0.0000 -423.3061	0.0000	0.0000	200.0042	0.0000	24.8731	0.0000	9.9493	-0.8954	0.0000	14.9239	-1.6416	-2.5371

Table 22. Op 4 As 3 Result from *Exp 1D* for Days 5 and 6

D	24h Pot S 24h Pot D		Ch	DisCh	BS	Offer	Ask	SellM	BuyM	TransM	SellG	BuyG	TransG	Payoff
5		0.0000 -493.0464	0.0000	0.0000	200.0042	0.0000	14.4454	0.0000	5.7782	-0.5200	0.0000	8.6673	-0.9534	-1.4734
		0.0000 -508.4784	0.0000	0.0000	200.0042	0.0000	12.0739	0.0000	4.8296	-0.4347	0.0000	7.2444	-0.7969	-1.2315
		$0.0000 - 522.5739$	0.0000	0.0000	200.0042	0.0000	11.3954	0.0000	4.5582	-0.4102	0.0000	6.8373	-0.7521	-1.1623
		0.0000 -534.1548	0.0000	0.0000	200.0042	0.0000	9.4633	0.0000	3.7853	-0.3407	0.0000	5.6780	-0.6246	-0.9653
		0.0000 -545.0987	0.0000	0.0000	200.0042	0.0000	8.4168	0.0000	3.3667	-0.3030	0.0000	5.0501	-0.5555	-0.8585
		$0.0000 - 556.3469$	0.0000	0.0000	200.0042	0.0000	9.7290	0.0000	3.8916	-0.3502	0.0000	5.8374	-0.6421	-0.9924
		0.0000 -565.3266	0.0000	0.0000	200.0042	0.0000	13.8367	0.0000	5.5347	-0.4981	0.0000	8.3020	-0.9132	-1.4113
		0.0000 - 571.0928	0.0000	0.0000	200.0042	0.0000	16.2395	0.0000	6.4958	-0.5846	0.0000	9.7437	-1.0718	-1.6564
		$0.0000 - 570.3883$	0.0000	0.0000	200.0042	0.0000	15.6559	0.0000	6.2624	-0.5636	0.0000	9.3935	-1.0333	-1.5969
		$0.0000 - 562.9390$	0.0000	0.0000	200.0042	0.0000	14.6732	0.0000	5.8693	-0.5282	0.0000	8.8039	-0.9684	-1.4967
		$0.0000 - 548.8568$	0.0000	0.0000	200.0042	0.0000	15.2232	0.0000	6.0893	-0.5480	0.0000	9.1339	-1.0047	-1.5528
		0.0000 -548.8855	0.0000	0.0000	200.0042	0.0000	14.3468	0.0000	5.7387	-0.5165	0.0000	8.6081	-0.9469	-1.4634
		0.0000 -538.0692	0.0000	0.0000	200.0042	0.0000	10.9460	0.0000	4.3784	-0.3941	0.0000	6.5676	-0.7224	-1.1165
		17.0358 - 527.1231	0.0000	0.0000	200.0042	0.0000	11.4347	0.0000	4.5739	-0.4116	0.0000	6.8608	-0.7547	-1.1663
		34.9834 - 515.6884	0.0000	0.0000	200.0042	0.0000	13.8048	0.0000	5.5219	-0.4970	0.0000	8.2829	-0.9111	-1.4081
		48.5625 - 501.8837	0.0000	0.0000	200.0042	0.0000	20.7481	0.0000	8.2992	-0.7469	0.0000	12.4489	-1.3694	-2.1163
		52.7407 - 481.1355	0.0000	29.9870	170.0172	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		52.7407 - 454.4157	0.0000	17.4796	152.5376	0.0000	8.0941	0.0000	3.2376	-0.4533	0.0000	4.8565	-0.8742	-1.3274
		52.7407 - 439.7028	0.0000	0.0000	152.5376	0.0000	34.4264	0.0000	13.7706	-1.9279	0.0000	20.6558	-3.7181	-5.6459
		52.7407 - 425.2984	0.0000	0.0000	152.5376	0.0000	38.4779	0.0000	15.3911	-2.1548	0.0000	23.0867	-4.1556	-6.3104
		52.7407 - 411.2928	0.0000	0.0000	152.5376	0.0000	39.7434	0.0000	15.8973	-1.4308	0.0000	23.8460	-2.6231	-4.0538
		52.7407 - 395.6749	0.0000	0.0000	152.5376	0.0000	39.0656	0.0000	15.6262	-1.4064	0.0000	23.4393	-2.5783	-3.9847
		52.7407 - 380.0583	0.0000	0.0000	152.5376	0.0000	38.2368	0.0000	15.2947	-1.3765	0.0000	22.9421	-2.5236	-3.9002
		52.7407 - 364.6141	0.0000	0.0000	152.5376	0.0000	35.1031	0.0000	14.0412	-1.2637	0.0000	21.0618	-2.3168	-3.5805

Table 23. Op 4 As 3 Result from *Exp 1D* for Day 7

D		24h Pot S 24h Pot D	Ch	DisCh	BS	Offer	Ask	SellM	BuyM	TransM	SellG	BuyG	TransG	Payoff
$\overline{\mathbf{z}}$		40.9982 - 387.0631	0.0000	0.0000	163.1058	0.0000	21.1070	0.0000	8.4428	-0.7599	0.0000	12.6642	-1.3931	-2.1529
		40.9982 - 365.9561	0.0000	0.0000	163.1058	0.0000	20.7743	0.0000	8.3097	-0.7479	0.0000	12.4646	-1.3711	-2.1190
		40.9982 - 345.1818	0.0000	0.0000	163.1058	0.0000	20.9619	0.0000	8.3848	-0.7546	0.0000	12.5771	-1.3835	-2.1381
		40.9982 - 324.2199	0.0000	0.0000	163.1058	0.0000	20.1477	0.0000	8.0591	-0.7253	0.0000	12.0886	-1.3298	-2.0551
		40.9982 - 304.0721	0.0000	0.0000	163.1058	0.0000	18.3878	0.0000	7.3551	-0.6620	0.0000	11.0327	-1.2136	-1.8756
		40.9982 - 285.6843	0.0000	0.0000	163.1058	0.0000	17.1955	0.0000	6.8782	-0.6190	0.0000	10.3173	-1.1349	-1.7539
		40.9982 - 268.4888	0.0000	0.0000	163.1058	0.0000	16.9189	0.0000	6.7675	-0.6091	0.0000	10.1513	-1.1166	-1.7257
		40.9982 - 251.5699	0.0000	0.0000	163.1058	0.0000	12.6498	0.0000	5.0599	-0.4554	0.0000	7.5899	-0.8349	-1.2903
		40.9982 - 238.9202	0.0000	0.0000	163.1058	0.0000	6.5891	0.0000	2.6356	-0.2372	0.0000	3.9535	-0.4349	-0.6721
		40.9982 - 232.3311	0.6551	0.0000	163.6954	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		40.3431 - 232.3311	10.0605	0.0000	172.7499	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		30.2826 - 232.3311	12.0897	0.0000	183.6306	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		18.1928 - 232.3311	13.3245	0.0000	195.6227	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		4.8683 - 232.3311	4.8683	0.0000	200.0042	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		0.0000 -232.3311	0.0000	0.0000	200.0042	0.0000	13.3075	0.0000	5.3230	-0.4791	0.0000	7.9845	-0.8783	-1.3574
		0.0000 -219.0236	0.0000	0.0000	200.0042	0.0000	11.2439	0.0000	4.4976	-0.4048	0.0000	6.7464	-0.7421	-1.1469
		0.0000 -207.7796	0.0000	0.0000	200.0042	0.0000	7.0937	0.0000	2.8375	-0.3972	0.0000	4.2562	-0.7661	-1.1634
		0.0000 -200.6859	0.0000	0.0000	200.0042	0.0000	18.7747	0.0000	7.5099	-1.0514	0.0000	11.2648	-2.0277	-3.0790
		$0.0000 - 181.9112$	0.0000	0.0000	200.0042	0.0000	28.0313	0.0000	11.2125	-1.5698	0.0000	16.8188	-3.0274	-4.5971
		0.0000 -153.8799	0.0000	0.0000	200.0042	0.0000	31.6426	0.0000	12.6570	-1.7720	0.0000	18.9856	-3.4174	-5.1894
		$0.0000 - 122.2373$	0.0000	0.0000	200.0042	0.0000	31.8016	0.0000	12.7206	-1.1449	0.0000	19.0809	-2.0989	-3.2438
	0.0000	-90.4357	0.0000	0.0000	200.0042	0.0000	31.2012	0.0000	12.4805	-1.1232	0.0000	18.7207	-2.0593	-3.1825
	0.0000	-59.2345	0.0000	0.0000	200.0042	0.0000	30.0601	0.0000	12.0240	-1.0822	0.0000	18.0361	-1.9840	-3.0661
	0.0000	-29.1744	0.0000	0.0000	200.0042	0.0000	29.1744	0.0000	11.6698	-1.0503	0.0000	17.5046	-1.9255	-2.9758

Table 27. Op 4 As 2 Result from *Exp 2S* for Day 7

Table 28. Op 4 As 3 Result from *Exp 3B* for Days 1 and 2

D	24h Pot S	24h Pot D	Ch	DisCh	BS	Offer	Ask	SellM	BuyM	TransM	SellG	BuyG	TransG	Payoff
$\mathbf{1}$	151.2558	-118.6801	0.0000	6.1356	193.8644	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.2558	-118.7079	0.0000	5.6359	188.2285	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.2558	-118.5514	0.0000	5.2747	182.9537	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.2558	-118.3695	0.0000	7.5986	175.3551	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.2558	-118.0244	0.0000	9.6465	165.7086	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.2558	-117.9787	0.0000	11.6987	154.0098	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.2558	-118.7062	2.2929	0.0000	156.0735	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	151.3701	-118.7062	6.3465	0.0000	161.7853	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	150.8473	-118.7062	9.3815	0.0000	170.2287	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	150.1100	-118.7062	13.0927	0.0000	182.0122	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	147.5734	-118.7062	19.0333	0.0000	199.1422	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	137.6091	-118.7062	27.8075	0.0000	224.1689	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	116.7920	-118.7062	20.0818	0.0000	242.2425	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	98.8471	-118.7062	16.7078	0.0000	257.2796	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	82.4328	-118.7062	12.4778	0.0000	268.5096	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	74.3949	-118.7062	10.8483	0.0000	278.2731	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	70.1917	-118.7062	8.0704	0.0000	285.5364	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	67.0272	-118.7062	5.1152	0.0000	290.1401	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	64.5421	-118.7062	0.0000	6.1934	283.9466	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	64.5421	-115.4379	0.0000	17.0788	266.8678	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	64.5421	-105.6770	0.0000	17.8468	249.0210	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	64.5421	-96.0120	0.0000	14.0877	234.9334	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	64.5421	-87.8284	0.0000	10.5863	224.3470	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	64.5421	-81.3312	0.0000	6.8969	217.4501	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

D 24h Pot S 24h Pot D Ch DisCh BS Offer Ask SellM BuyM TransM SellG BuyG TransG Payoff 3 73.3413 -70.1624 0.0000 2.5264 195.8427 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 73.3413 -71.8946 0.0000 2.4393 193.4034 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 73.3413 -73.1996 0.0000 2.4097 190.9936 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 73.3413 -74.4453 0.0000 3.3751 187.6186 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 73.3413 -76.9617 0.0000 4.6531 182.9654 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 73.3413 -80.4269 0.0000 6.6421 176.3233 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 73.3413 -84.8622 1.5879 0.0000 177.7523 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 74.0645 -84.8622 3.8122 0.0000 181.1833 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 76.8761 -84.8622 5.4452 0.0000 186.0840 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 81.9144 -84.8622 11.2996 0.0000 196.2536 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 83.8410 -84.8622 18.2753 0.0000 212.7014 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 85.8004 -84.8622 7.1999 0.0000 219.1812 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 95.7919 -84.8622 4.6175 0.0000 223.3370 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 107.6747 -84.8622 4.2637 0.0000 227.1743 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 110.4162 -84.8622 1.5143 0.0000 228.5372 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 113.6188 -84.8622 6.3822 0.0000 234.2811 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 108.2888 -84.8622 5.0932 0.0000 238.8650 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 108.0122 -84.8622 3.8505 0.0000 242.3304 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 106.3490 -84.8622 0.0000 4.4393 237.8911 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000

Table 29. Op 4 As 3 Result from *Exp 3B* for Days 3 and 4

106.3490 -84.1010 0.0000 12.0992 225.7919 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 106.3490 -82.5032 0.0000 11.9000 213.8919 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 106.3490 -81.6293 0.0000 8.2035 205.6884 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 106.3490 -81.1614 0.0000 6.4999 199.1885 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 106.3490 -80.1839 0.0000 4.9746 194.2138 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000

A.3 Daily and Weekly Internal Selling Price, Internal Buying Price and Diff

Table 32. Daily and Weekly ISP, IBP and Diff for *Exp 1D* (in £/kWh)

Table 33. Daily and Weekly ISP, IBP and Diff for *Exp 2S* (in £/kWh)

Daily	ISP ₁	IBP ₁	Diff 1	ISP ₂	IBP ₂	Diff ₂	ISP ₃	IBP ₃	Diff 3	ISP ₄	IBP ₄	Diff ₄	ISP ₅	IBP 5	Diff 5
	0.0716	0.0750	0.0034	0.0625	0.0575	-0.0050	0.0671	0.0663	-0.0008	0.0694	0.0706	0.0013	0.0682	0.0684	0.0002
	0.0709	0.0750	0.0041	0.0617	0.0575	-0.0042	0.0663	0.0663	0.0000	0.0686	0.0706	0.0021	0.0674	0.0684	0.0010
	0.0724	0.0750	0.0026	0.0632	0.0575	-0.0057	0.0678	0.0663	-0.0016	0.0701	0.0706	0.0005	0.0690	0.0684	-0.0005
	0.0717	0.0750	0.0033	0.0625	0.0575	-0.0050	0.0671	0.0663	-0.0008	0.0694	0.0706	0.0012	0.0682	0.0684	0.0002
	0.0678	0.0750	0.0072	0.0587	0.0575	-0.0012	0.0632	0.0663	0.0030	0.0609	0.0619	0.0009	0.0598	0.0597	-0.0001
	0.0715	0.0750	0.0035	0.0623	0.0575	-0.0048	0.0669	0.0663	-0.0007	0.0692	0.0706	0.0014	0.0681	0.0684	0.0004
	0.0749	0.0750	0.0001	0.0657	0.0575	-0.0082	0.0703	0.0663	-0.0040	0.0726	0.0706	-0.0020	0.0737	0.0728	-0.0009
Weekly	0.0713	0.0750	0.0037	0.0622	0.0575	-0.0047	0.0668	0.0663	-0.0005	0.0691	0.0706	0.0016	0.0679	0.0684	0.0005

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