Game theory based power flow management in a peer-to-peer energy sharing network

by

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SUMMARY

GAME THEORY BASED POWER FLOW MANAGEMENT IN A PEER-TO-PEER ENERGY SHARING NETWORK

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In deregulated electricity markets, profit driven electricity retailers compete to supply cheap reliable electricity to electricity consumers, and the electricity consumers have free will to switch between the electricity retailers. The need to maximize the profits of the electricity retailers while minimizing the electricity costs of the electricity consumers has therefore seen a drastic increase in the research of electricity markets. One of the factors that affect the profits of the electricity retailers and the energy cost of the consumers in electricity retail markets is the supply and demand. During high-supply and low-demand periods, the excess electricity if not managed, is wasted. During low-supply high-demand periods, the deficit supply can lead to electricity blackouts or costly electricity because of the volatile electricity wholesale spot market prices. Research studies have shown that electricity retailers can achieve significant profits and reduced electricity costs for their electricity consumers by minimizing the excess electricity and deficit electricity. Existing studies developed load forecasting models that aimed to match electricity supply and electricity demand. These models reached excellent accuracy levels, however due to the high volatility character of load demand and the rise of new electricity consumers, load forecasting alone is unable to mitigate excess and deficit electricity. In other studies, researchers proposed charging the electricity consumers' batteries with excess electricity during high-supply low-demand periods and supplying their deficit electricity during low-supply high-demand periods.

Electricity consumers' incorporating batteries resulted in minimized excess and deficit electricity, in turn, maximizing the profits for the electricity retailers and minimizing the electricity costs for the electricity consumers. However, the batteries are consumer centric and only provide battery energy for the battery-owned consumer. Electricity consumers without battery energy during low-supply high-demand periods have electricity blackouts or require costly electricity from the electricity wholesale spot market. The peer-to-peer (P2P) energy sharing framework which allows electricity consumers to share their energy resources with one another is a viable solution to allow electricity consumers to share their battery energy. P2P energy sharing is a hot topic in research because of its potential to maximize the electricity retailers' profits and minimize the electricity consumers' electricity costs.

Due to the increased profits for the electricity retailer and reduced electricity costs for the electricity consumers from implementing battery charging and P2P energy sharing, this dissertation proposes a day-ahead electricity retail market structure in which the electricity retailer supplies consumers' batteries with excess electricity during high-supply low-demand periods, and during low-supply high-demand periods the electricity retailer discharges the consumers' batteries to supply their deficit supply or supply their peers' deficit supply. The electricity retailer aims to maximize its profits and minimize the electricity cost of the electricity consumers in its electricity retail market, by minimizing the excess and deficit electricity. The problem is formulated as a non-linear optimization model and solved using game theory.

This dissertation compares the profits of the electricity retailer and electricity costs of the consumers that charge their batteries with excess electricity, discharge their batteries and purchase electricity from their peers to supply their deficit supply, with consumers that only charge their batteries with excess electricity but do not share their battery energy with their peers, consumers that only purchase electricity from their peers to supply their deficit supply but do not employ a battery, and consumers that neither employ a battery nor purchase electricity from their peers to supply their deficit supply. The results show that the consumers that charge their batteries with excess electricity, discharge their batteries and purchase electricity from their peers to supply their deficit supply achieved the lowest electricity cost and highest profits for the electricity retailer.

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LIST OF ABBREVIATIONS

AUD	Australian dollar
ANN	Artificial neural network
b^c	Battery charging energy (kWh)
BESS	Battery energy storage system
BSM	Bill sharing model
Δt	Sampling interval
DER	Distributed energy resources
DER	Distributed energy resource
$d_{i,t}^p$	Deficit supply after self-discharge and P2P energy sharing (kWh)
$E_b(i_j,t)$	Available energy in BESS of consumer i_j (kWh)
ESC	Energy sharing coordinator
ESS	Energy storage systems
EV	Electric vehicle
FIT	Feed in tariff
ISO	Independent system operator
I_j	Total number of type j consumers
i_j	Index of consumer i of the jth type: $i_j = 1,2,\ldots,I_j$
j	Index of consumer types, $j = 1,2,3,4$
k	Constant parameter
LFC	Load frequency control
LTLF	Long-term load forecasting
MMRM	Mid-market rate model
MTLF	Mid-term load forecasting
η_c, η_d	Charging and discharging efficiency of consumer i_j BESS
RES	Renewable energy source
$R_g(t)$	Griding selling price of forecast electricity (c/kWh)
$R_g^u(t)$	Griding selling price of unforecasted electricity (c/kWh)
$R_p^u(t)$	Retailer selling price of unforecast electricity (c/kWh)
RTP	Real-time price
P2G	Peer-to-grid

P2P	Peer-to-peer
$P^d_{b,T}(t)$	Total discharging power from all consumers' BESSs (kW)
$P_{buy}(i_j,t)$	Power bought by consumer i_j through P2P (kW)
$P_b(i_j,t)$	Available battery power for sell to peers by consumer i_j (kW)
$P_d(i_j,t)$	Power supply deficit of consumer i_j after self-supply (kW)
$P^c_b(i_j,t)$	Charging power consumer i_j BESS (kW)
$P^d_b(i_j,t)$	Discharging power consumer i_j BESS (kW)
PFC	Primary frequency control
$\hat{P}(i_j,t)$	Forecasted power demand of the consumer i_j (kW)
$P(i_j,t)$	Actual power demand of the consumer i_j (kW)
$P_e(t)$	Excess/deficit power in the electricity retail market at time t (kW)
$P_{sell}(i_j,t)$	P2P selling power of i_jth consumer's BESS (kW)
$\hat{P}_T(t)$	Total forecast demand of all consumers (kW)
$\bar{R}_p(t)$	Retailer selling price of electricity when there is surplus supply (c/kWh)
$R_p(t)$	Retailer time-of-use selling price of electricity (c/kWh)
RES	Renewable energy sources
SFC	Secondary frequency control
SDR	Supply and demand ratio
$SDR(t)$	Supply demand ratio
SDRM	Supply and demand ratio model
SOC	State of charge
STLF	Short-term load forecasting
t	Time index (hour)
TOU	Time-of-use
$v(i_j,t)$	Strategy of consumer i_j participating P2P game
$v(-i_j,t)$	Strategies of all consumers other than consumer i_j participating P2P game
VSTLF	Very short-term load forecasting
$x^c_b(i_j,t)$	Binary variable, equals to one when consumer i_j BESS is charging and zero otherwise
$x^c_b(-i_j,t)$	Strategies of all consumers other than consumer i_j participating battery charging game
$x_{buy}(i_j,t)$	Binary variable, equals to one when consumer i_j is buying P2P electricity and zero otherwise
$x_{sell}(i_j,t)$	Binary variable, equals to one when consumer i_j is selling P2P electricity and zero otherwise
$x^d_b(i_j,t)$	Binary variable, equals to one when consumer i_j BESS is discharging and zero otherwise
λ	Compensating price to encourage P2P selling (c/kWh)

$z_b(i_j,t)$	Commulative expenditure of consumer i_j for keeping his/her battery with $E_b(i_j,t)$ (c)
$z_{buy}(t)$	P2P buying price (c/kWh)
$z_p(t)$	Equivalent price of electricity stored in consumer BESSs (c/kWh)
$z_{sell}(t)$	P2P selling price (c/kWh)

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION

1.1 CHAPTER OVERVIEW

This chapter introduces the day-ahead electricity retail market structure in which the electricity retailer supplies consumers' batteries with excess electricity during high-supply low-demand periods, and discharges the consumers' batteries to either or both self-supply and peer-supply during the low-supply high-demand periods, for the purpose of maximizing the retailer's profits and minimizing the consumers' electricity cost. The context of the problem, the research objectives, research questions, research goals and contribution are put forward. The hypothesis, study approach and the the layout of the study are also presented in this chapter.

1.2 PROBLEM CONTEXT AND MOTIVATION

In an electricity wholesale market, power producers contractually commit to supply specified capacities of electricity at predetermined wholesale electricity prices ahead of delivering time over years and months (i.e future markets), days (i.e day-ahead markets), hour, minutes and seconds (i.e intra-day markets) [1, 2]. The wholesale electricity is either directly consumed by large commercial and industrial consumers or supplied to small consumers by electricity retailers at a resale price [3, 4]. The electricity retailers usually prioritise the retail electricity prices for their maximum profits, and in the meantime set the retail electricity prices to be competitive against other retailers to attract more consumers.

It is crucial for retailers to understand the structure of electricity pricing in an electricity market. In the wholesale market, electricity usually trades at a real-time price (RTP) mechanism [5]. The RTP can be highly profitable for retailers, however it can also be costly due its ability to vary dramatically. The

RTP varies due to unexpected changes in consumer demand and availability of electricity generating resources. The RTP typically drops when demand is low and/or generating resources are in abundance, however it rises fast when demand is high and/or generating resources are scarce [6]. Due to the high price risks of the RTP, it is difficult to be accepted by small consumers [7]. To protect small consumers from the price volatility of the RTP, electricity retailers step in as an intermediary between electricity producers and consumers to alleviate these risks. An electricity retailer can either be an independent private third-party or an electricity distribution entity belonging to a power supply company such as a local government municipality [7]. The electricity retailers handle price risks by well designed retail prices with knowledge from advanced load forecasting for both power supply and consumers' total power demand, which is often inaccessible to small consumers [8]. The design of retail prices takes into account the wholesale market costs, retailing costs, transmission and distribution network costs, and the environmental policy costs [9]. The electricity retail market prices are typically predetermined, robust and changed infrequently. Four main types of retail prices have been widely used, namely 1) hourly retail prices; 2) daily retail prices that are either determined a day-ahead or an hour-ahead; 3) time-of-use (TOU) prices; and 4) seasonal flat prices that are determined months-ahead [6]. The TOU provides the consumers with great potential to reduce their electricity cost by shifting their loads from high prices periods to low price periods. Hourly and daily retail prices are announced near the electricity consumption time, posing some uncertainty for consumers to shift their loads, while consumers under a seasonal retail tariff have no motivation to shift their loads [6]. Due to the superior advantage to boost load shifting for peak load reduction, the TOU tariff has been the most adopted retail pricing scheme in practice [5, 7, 8]. Existing studies show that consumers can reduce their electricity cost by 11%, by adopting a TOU pricing scheme [5, 6].

In addition to prioritising the retail pricing, electricity retailers always have to enhance their ability of load forecasting. Retailers protect single consumers from load volatility risks by conducting their total load forecasting as an aggregated unit. Thus the load forecasting errors of single consumers cancel out, which results in lower overall load volatility risks. Using consumer's real time power demand data from smart meters, retailers are able to gain a better understanding of customer loads and mitigate excess exposure to load volatility risks [8]. The accuracy of retailer load forecasting affects the electricity tariff, thus a retailer is concerned with load forecasting to mitigate excess electricity. Electricity cannot be cost-effectively stored in the electrical transmission network and excess electricity is wasted. Existing studies show that various energy storage systems (ESS) on the demand-side are capable of effectively balancing supply and demand at finer time scales. BESS is found to respond faster to load changes with high energy efficiency up to 95%, which is favourable in enhancing the system stability. In 2017 BESS on the demand-side held 11 GWh of the total ESS worldwide and has a predicted growth rate of 100 GWh to 167 GWh in 2030 [10]. BESS have gradually gained popularity as measures for retailers to increase their profits and for consumers to reduce their electricity costs. Previous studies show that consumers implementing batteries can decrease their electricity expenditure by 40% [11], additionally consumer BESS can relieve the distribution grid by 20% of excess electricity by adopting a charging strategy [12]. It is evident that BESS not only maximize their capacities with excess electricity to ensure a supply of loads during low-supply high-demand periods, but also improves the financial aspect of consumers [13]. To improve the financial position of consumers, the cost of the BESS is important to consider. The cost of a battery is a sum of two main costs, the BESS investment cost and the BESS operating cost [14]. The investment cost and operating cost are both influenced by the size of the BESS. It is therefore paramount to optimally size the BESS that minimizes investment and operational costs, as to improve the financial position of consumers [14, 15]. Various BESS optimal sizing studies have been conducted to improve the cost of the consumers. An optimal sized BESS of 800 kWh installed in [13] profited the microgrid by $706, compared to microgrid without a BESS. In [16], an optimal sized BESS provided less than $80/kWh/yr worth of energy exchange with grid for consumers, compared to $1,078.50/year for consumers without a BESS. The investment cost of a BESS relates to the BESS technology, which affects the life cycle of the BESS. Studies show that lithium-ion batteries provide high operational efficiency that reduce the system operational cost, however they have high investment costs, in comparison to lead-acid BESS. Because of their high operating efficiency, lithium-ion BESS optimally sized in [17] decreased the power losses by 61.38 kW for single BESS, resulting in a minimized BESS cost.

In other studies that sought to minimize excess electricity, the electricity retailers allowed prosumers to trade the excess electricity from their energy resources. In the past, prosumers traded the excess electricity from their renewable energy sources (RES) with the electrical grid in the peer-to-grid (P2G) energy sharing framework. However, the rise in RESs that are sporadic in nature result in stochastic excess electricity. The excess electricity presents additional tasks to balance supply and demand in the already complex operation of grid. Existing studies show that for every 10% adoption of a RES, an additional 2% to 4% of power is required to balance supply and demand of the electrical grid [18]. Peer-to-peer (P2P) energy sharing was introduced in recent years to improve the drawback of P2G energy sharing. The P2P energy sharing is the process through which electricity prosumers sell their excess electricity directly to their neighbours [19, 20]. Potential benefits of P2P energy trading include consumer electricity cost reduction and retailer profits increments. An existing study shows that P2P energy sharing is able to reduce the electricity cost of the community by 30% compared to the conventional P2G energy sharing, and it increases annual self-consumption by 10-30%, and self-sufficiency by 20% [21]. Although the P2P can provide significant reduced electricity costs, the challenges to improve the P2P energy trading framework and engage more prosumers remains a topic of interest in research. This study tackles this challenge by proposing a game theory based P2P energy sharing platform where participants can trade their stored BESS energy. The operation of P2P energy sharing is typically managed by an energy service coordinator (ESC). In order to encourage P2P energy sharing participation, the ESC regulates consumer electricity trading behaviour by internal P2P electricity prices [20, 22]. In the P2P energy sharing networks whereby prosumers directly trade the excess electricity from their RES, the P2P electricity prices are bounded by the electricity import and export prices of a microgrid. The electricity price of importing electricity from neighbouring consumers is lower than importing electricity from the electrical grid, and exporting electricity to neighbouring prosumers returns higher profits than exporting electricity to the electrical grid [22]. The P2P energy sharing allows prosumers employed with BESS to trade energy BESS energy, and the pricing principle to economically benefit prosumers is the same as the P2P energy traded directly from RES. The P2P electricity prices are formulated either by bill sharing mechanism (BSM), mid-market rate mechanism (MMRM) or by supply and demand ratio mechanism (SDRM). The BSM sums and shares the electricity cost of the electricity traded among all the prosumers in a microgrid and the electrical grid, according to each prosumers' proportion of generation and consumption. The shared energy between peers is not billed in the BSM, therefore prosumers are encouraged to meet their supplies with P2P energy sharing and export energy to the grid to minimize their electricity cost and increase their profits, respectively. In the MMRM, the P2P price is the middle price of importing electricity from the electrical grid and the middle price of exporting electricity to the electrical grid. The P2P energy sharing price in the SDRM is determined by the electricity are prosumers are buying and selling inside the microgrid. The study in [23] performed an analysis in terms of the value tapping, the consumers willingness to participate, ability to balance internal supply and demand, flattening the power curve and ability to self supply. In the analysis, the BS show the lowest performance, the MMRM show good performance when with moderate PV penetration levels between 10% to 60% and the SDRM outperforms the BSM and MMRM from an economic and technical point of view. Due to the high performance of SDRM, this study implements a SDR price mechanism for consumers in competition to achieve the low P2P energy sharing prices using game theory. Game theory is a great optimization tool when interdependence of game participants is considered [24]. The consumers in the retail market will compete for affordable electricity in a non-cooperative game. Game theory is an optimal decision-making tool for independent, rational thinking and competing participants who strive to maximize their individual outcomes in a strategic setting containing a set rules and outcomes. This is because consumers are generally selfish in the real world, and coalitions between them are often difficult to form. Game theory provides an optimal solution for consumers without coalitions by optimally make decisions of independent and competing players [25].

For the electricity power grids in many countries, power supply is still based on large-scale coal fired power generation units. Given that most coal fired power plants are far away from the end users, large scale power transmission and distribution networks have to be built, which also result in that only large companies or government municipalities have the capacity to trade electricity to each distribution network contains over millions of consumers. In future electricity markets, due to the prosperity of distributed power generation with renewable energy resources, business models of electricity retailers will be more flexible that allows small business owners to buy and sell electricity to consumers in one or several communities. In this study, we aim to obtain the optimal benefits for the small scale electricity retailers in a distributed power generation network. Without loss of generality, we consider a electricity retailer who buys electricity from the wholesale market and then resells the electricity to consumers in one community. The retailer buys electricity at a wholesale market price on daily basis from the wholesale market according to the load forecasting outcome on the daily load profile of the community. Due to load forecasting errors, the retailer sometimes buys more electricity than the actual power demand. The excessive electricity from the retailers are usually wasted since he does not have an energy storage system. Sometimes, the retailer buys less electricity than the actual power demand in the community, then he has to buy some emergency power from the wholesale electricity market, at an extremely high price according the agreement between the retailer and the wholesale market. As the retailer is a small business owner, he does not have the technical strength to further improve the load forecast accuracy, and he cannot afford to invest on his own battery energy storage systems. In order to maintain his profit while offering satisfactory service, he encourages the users to install their own batteries. Previously, the retail price for this community follows a day-ahead electricity price mechanism. More precisely, the retailer announces an hourly electricity price for the next 24 hours one day ahead. Now in order to build a win-win business model with this community, this retailer implements two battery operation schemes. Firstly, the community enters a battery charge mode when the retailer supplies excessive electricity. In this mode, the retailer encourages the customers to charged their batteries at a lower price than normal retailer price. Secondly, the community enters a peer-to-peer energy sharing mode when the retailer fails to supply sufficient power against the total power demand. In the P2P energy sharing mode, the consumers are allowed to trade the energy stored in their batteries to other peer consumers at a internal P2P trading price. In both modes of battery charging and P2P energy sharing, the consumers enter into a competition to minimise their electricity expenditure. The competition is analysed in a non-cooperative Nash equilibrium game theory as the consumers are considered as selfish but rational players. Obviously, the retailer cannot force each consumer to buy batteries and join the two battery operation schemes. Then the consumers are naturally classified into four categories, namely 1) customers without batteries who are not interested in interested in P2P energy sharing; 2) customers without batteries who are interested in energy sharing; 3) customers with batteries who join the charging mode but not participate in the P2P energy sharing mode; and 4) customers with batteries who join both the charging mode and the P2P energy sharing mode.

The results from this study show that customers that joined both charging and P2P energy sharing modes resulted in an overall lower energy cost, because unlike the other customers, they required less of the high priced emergency electricity. It was also interesting to find out that customers with batteries who join the charging mode but not participate in the P2P energy sharing mode achieve low energy costs if they have a lot deficit supply. This is because they reserved their BESS energy for self-supply instead of selling it, as it is cheaper to self-supply than buy energy from peers in the community. Customers without batteries who are interested in energy sharing were found to be better off than customers without batteries who are not interested in interested in P2P energy sharing, because a portion or all of their deficit supply is settled by shared energy, which is cheaper than the emergency electricity.

1.3 RESEARCH OBJECTIVE AND QUESTIONS

The main research objective of this dissertation is to develop an optimization model that simultaneously maximizes the profits of the electricity retailer and minimizes the electricity cost of the electricity consumers in an electricity retail market. Maximizing the profits of the electricity retailer and minimizing the electricity cost of the electricity consumers is based on minimizing the excess and deficit electricity, a result of load forecasting in a day-ahead electricity retail market. To achieve this objective, the following specific objectives are stated:

1. To investigate the effects of charging consumers' BESS with excess electricity during high-supply low-demand periods and discharging consumers' BESS during low-supply high-demand periods on the energy costs of the consumers.
2. To validate the electricity cost saving potential for the consumers charging their BESS with excess electricity during high-supply low-demand periods and discharging consumers' BESS during high demand periods.
3. To validate the electricity retail profits achieved from consumers in the retail market charging their BESS with excess electricity during low demand periods and discharging consumers' BESS during low-supply high-demand periods.

In order to achieve the objectives listed above, this dissertation addresses the following research questions:

1. What are the electricity cost saving advantages for consumers who charge their BESS with excess electricity during high-supply low-demand periods, discharge them during low-supply high-demand periods and purchase electricity in the P2P energy sharing network during during low-supply high-demand periods, compared to 1) consumers that only charge their BESS with excess electricity during high-supply low-demand periods and discharge them during low-supply high-demand periods, 2) consumers that only purchase electricity in the P2P energy sharing network during low-supply high-demand periods and 3) consumers that neither charge their BESS with excess electricity during high-supply low-demand periods, discharge their BESS during low-supply high-demand periods, nor purchase electricity in the P2P energy sharing network during during low-supply high-demand periods?
2. What are the electricity retail profit advantages achieved from minimizing excess and deficit electricity by electricity consumers charging their BESS with excess electricity during high-supply low-demand periods and discharging them during low-supply high-demand periods?

1.4 HYPOTHESIS AND RESEARCH APPROACH

This dissertation develops an electricity regulation model for an electricity retailer operating a day-ahead electricity retail market that aims to maximise the economic value of the electricity retailer and electricity consumers. To achieve the aim of the electricity regulation model, the electricity retailer mitigates electricity wasting and unforecasted electricity by allowing excess electricity BESS charging and P2P energy sharing. The following hypotheses are stated:

1. Electricity retailer supplying consumer BESS with excess electricity alleviates electricity waste, minimizes the electricity cost of the electricity consumers and maximizes the profits of the electricity retailer.
2. Electricity retailer allowing P2P energy sharing during low-demand high-demand periods alleviates unforecasted electricity trading, minimizes the electricity cost of the electricity consumers and maximizes the profits of the electricity retailer.
3. Integrating BESS excess electricity charging during high-supply low-demand periods with P2P energy sharing during low-supply high-demand periods yields more profits for the electricity retailer than profits achieved either from only BESS electricity charging or only P2P energy sharing.
4. Integrating BESS excess electricity charging during high-supply low-demand periods with P2P energy sharing during low-demand high-demand periods yields less electricity costs for the electricity consumers, than electricity costs achieved either from only BESS electricity charging or only P2P energy sharing.

This research work uses the following approaches to achieve the aforementioned research objectives:

- Literature review - A literature study on the existing electricity regulation models in an electricity market particularly those implemented using BESS and P2P energy sharing will be carried out to establish a body of knowledge related to the proposed system in this study.
- Mathematical model formulation - Mathematical models that characterize the operation of each of the sub-systems of the proposed electricity regulation model are developed.
- Results - An optimisation model that optimally maximizes the profits of the retail market and minimizes the electricity costs of the consumers in an electricity retail market is developed and validated by application of a suitable real life case study. The simulation results are compared with the existing electricity regulation models.
- Discussions - The results are discussed and the conclusions are drawn from hem.

1.5 RESEARCH GOALS

This research aims at achieving two main goals;

1. To present a BESS excess electricity charging pricing model and a P2P energy sharing pricing model that motivates the electricity consumers to charge their BESS with excess electricity and participate in P2P energy sharing network. The pricing models will intend to minimize the daily consumer electricity costs and maximize the daily electricity retailer profits.
2. To present a game theoretical model for the electricity consumers to compete for the excess electricity and compete to meet deficit supply with electricity traded in the P2P energy network. Game theory will intend to alleviate excess electricity and deficit electricity as to regulate the electricity in the electricity retail market.

1.6 RESEARCH CONTRIBUTION

The main contribution of this dissertation is integrating BESS excess electricity charging during lower demand periods with P2P energy sharing during higher demand periods which simultaneously maximizes the profits of the electricity retailer and minimizes the electricity cost of the electricity consumers. In the course of this research study, the following papers was developed:

1. Juliana Nepembe, Xianming Ye, Xiaohua Xia,Game Theory Based Power Flow Management in a Peer-to-Peer Energy Sharing Network, 9th International Conference on Applied Energy-ICAE2019, October 16-18 2019, Xiamen, China.

1.7 OVERVIEW OF STUDY

Chapter 1 introduces the background of the study. The research motivation, objectives, questions and goals are also presented, as well as a brief overview of the approach followed in this dissertation.

Chapter 2 reviews the current literature on electricity market operations to establish the relevant knowledge on electricity regulation techniques in the retail markets. The literature review, finds the research gap that has been addressed in this dissertation.

Chapter 3 presents an electricity regulation system for a retail electricity market. The main objective of this chapter is establishing the performance advantages of Integrating BESS excess electricity charging during lower demand periods with P2P energy sharing during higher demand periods over the existing singularly operated BESS excess electricity charging and P2P energy sharing.

Chapter 4 presents the simulation results and analysis of the electricity regulation system presented in Chapter 3.

Chapter 5 presents a discussion of the results.

Chapter 6 presents the conclusion for this study and presents several recommendations for future research directions.

CHAPTER 2 LITERATURE STUDY

2.1 CHAPTER OBJECTIVES

This chapter presents an overview of the existing literature on electricity retailer profit maximizing and consumer electricity cost minimization mechanisms in an electricity retail market. The first section presents an overview and structure of a typical electricity market. In chapter 1, charging electricity consumers' battery energy storage systems with excess electricity was identified as a technique to reduce the consumers' electricity cost and increase the profits of the electricity retailer. Chapter 1 also identified the peer-to-peer energy sharing framework as a technique to minimize consumer electricity cost and maximize the profits of the electricity retailer. This chapter introduces a general literature on battery energy storage systems and peer-to-peer energy sharing with respect to minimizing the electricity cost of electricity consumers and maximizing the profits of the electricity retailers in a electricity retail market.

2.2 OVERVIEW OF ELECTRICITY MARKETS

Electricity markets are systems that enable buying electricity, through bids, selling electricity through offers and trading electricity through obligation contracts within regional boundaries [26]. Electricity markets connect electricity generators and wholesale consumers in an electricity wholesale market [27]. Even though electricity markets are specific to a country, every electricity market has two main objectives, to ensure a secure electrical network and to facilitate the economics of trading, buying and selling electricity. A secure electrical network provides a perpetually continuous electricity supply to the electricity consumers. A continuous electricity supply is however infeasible as electricity demand widely varies on hour to hour basis throughout the year, and often electricity providers cannot accurately predict the demand to meet it. Studies show that electricity storages provide a viable solution to mitigate the varying load demand, however, electricity storage, particularly in large quantities is highly expensive, and hence electricity generated is to be consumed instantly [28, 29]. Consuming all electricity generated presents a challenge in electricity markets because of the volatile electricity load demand. Balancing electricity supply and electricity demand is therefore a complex task in electricity markets which affects the electricity prices. Electricity prices in electricity markets are designed to be affordable for the electricity consumers and simultaneously provide adequate profits for the electricity providers. These electricity price objectives enhance the complex structure of electricity markets. various participants of an electricity market (electricity generators, wholesale electricity market, retail electricity market and electricity consumers) play dynamic roles on obtaining the optimal electricity prices.

Electricity generators contractually commit years and months (i.e future markets), days (i.e day-ahead markets), hours, minutes and seconds (i.e intra-day markets) ahead of delivering time to supply given volumes of electricity at predetermined wholesale electricity prices [1, 2]. The electricity generators include nuclear power plants, hydroelectric power plants, solar and wind farms. These generating power plants all have the same objective; to maximise their economic profits from trading electricity in a wholesale electricity market. The electricity in a wholesale electricity market is traded either through electricity pools or through bilateral contracts. In electricity pools, wholesale electricity consumers have minimal input in the volume of electricity produced by the generators, as well as a minimum input in the price of electricity traded. However, in bilateral contracts, contractual agreements between the electricity generators and wholesale electricity consumers are set it place on the amount of electricity required and the cost of electricity [30].

Wholesale electricity markets allow electricity generators to trade electricity with electricity retailers and large consumers, using wholesale electricity prices [3, 4]. Large consumers such as large manufacturing industries, in countries such as United Kingdom, United States of America and Australia [31] are allowed to purchase electricity from their wholesale electricity markets. Electricity in the wholesale electricity market usually trades at a real-time price (RTP) mechanism [5]. The RTP is based on the availability of generating resources and the electricity demand from the electricity retailers and the large consumers. The RTP provides economical benefits to both the electricity generators and wholesale electricity consumers at an abundance of generating resources, however the RTP rises exponentially when electricity demand is high and/or generating resources are scarce, decreasing the economical benefits of the wholesale electricity market participants [6]. The RTPs have an ability to vary dramatically on an hourly basis. Existing studies show that changes in consumer demand and generating resources can lead to high wholesale price of $0.2/kWh [6]. Generally, average wholesale electricity prices are more affordable than retail electricity market prices, however buying electricity directly from the wholesale electricity market is subject to more electricity market uncertainty, membership costs, start up costs, insurance costs and organization costs. Due to the high electricity price risks in the wholesale electricity market, it has not entirely been accepted by small consumers with an annual electricity consumption below 2000 MWh [7, 32]. To protect small consumers from the price volatility of RTPs, electricity retailer maekets step in as intermediaries between electricity generators and electricity consumers, as to manage these price risks.

Retail electricity markets comprise of electricity consumers managed by an electricity retailer. In deregulated electricity markets, electricity retailers are independent private third-parties from the electricity generators, and in regulated electricity markets, electricity retailers are the electricity distribution entities such as a local government municipality belonging to a power supply company that generates the electricity [7]. The electricity retailers are provide electricity to the small-scale consumers that do not directly trade electricity in the wholesale electricity market [33]. Electricity retailers are profit driven and aim to maximize their profits through electricity resale. Electricity retailers purchase electricity in the wholesale electricity market at wholesale prices, re-price the electricity and sells it directly to the electricity consumers who consume the electricity. Several electricity retailers trading in the same wholesale electricity market, particularly in deregulated electricity markets, are in competition for the electricity consumers. To increase the number of electricity consumers in their electricity retail markets, electricity retailers aim to provide optimal electricity prices. The electricity retailers therefore strategize the retail electricity prices that provide optimal profits and optimal electricity costs for the consumers [8]. Retail electricity prices are based on electricity supply and demand as electricity retailers are accountable for the electricity imbalance provided by load forecasting in the retail market [1]. In previous studies, electricity retailers used pricing mechanisms or technical solutions to reduce peak demand, reduce supply and demand discrepancies, reduce the electricity cost of consumers and improve the retailer's profits [19]. The design of retail prices takes into account the wholesale market costs, retailing costs, transmission and distribution network costs, the environmental policy costs [9].

Electricity retail market prices are typically predetermined, robust and change less frequently. Four main types of electricity retail prices have been proposed in previous studies, hourly electricity retail tariff, daily electricity retail tariff, time-of-use (TOU) electricity retail tariff and seasonal flat electricity retail tariff [6]. Hourly electricity retail tariff vary on an hourly basis in attempt to reflect the RTP of the wholesale electricity market and they are announced anywhere from a day-ahead to the real-time of delivering electricity [34]. Daily electricity retail tariff are fixed during certain periods of time during the day, but the electricity retail price in some time periods have the potential to vary either occasionally or regularly [6]. The daily electricity retail tariff are fixed for months, however the varying price are announced anywhere from a day-ahead to an hour ahead of delivering electricity. TOU electricity retail tariff are fixed within each TOU pricing period. The TOU pricing period include a time of day, such as high-peak demand period, standard-demand periods and off-peak demand periods, day of the week such as weekdays and weekends and season, such as summer and winter [35]. TOU electricity retail tariff are announced months ahead of real-time electricity delivery and remain fixed for several months. Seasonal flat electricity retail tariff are fixed within one season such as summer or winter [6]. Seasonal electricity retail tariff are announced months ahead of real-time electricity delivery and remain fixed for several months.

Studies show that all four electricity retail tariff structures allow electricity consumers to perform load shifting reduce their electricity cost, however the TOU electricity retail tariff provides the highest incentives for the electricity consumers to shift their load [6]. Hourly and daily electricity retail tariff are announced close to the electricity consumption time, posing some uncertainty for consumers to shift their loads, while consumers under a seasonal retail tariff have no incentive to shift their loads in one season [6]. Due to the high incentive for consumers under the TOU tariff, the TOU tariff has been the most adopted retail pricing scheme in practice [5, 7, 8]. Existing studies show that electricity consumers can reduce their electricity cost by 11%, when they adopt a TOU pricing scheme [5, 6]. As mentioned earlier, in addition to effective retail pricing, electricity retailers face the problem of consumer load forecasting as well. Electricity retailers protect single consumers from load volatility risks by aggregating multiple consumers and conducting their total load forecasting as a single unit. Load forecasting performed for multiple consumers as a single unit results in load forecasting errors of single consumers cancelling out, and thus results in overall lower load volatility risks. Using consumer load pattern data from smart meters, retailers are able to gain a better understanding of customer loads and mitigate excess exposure to load volatility risks [8]. The success of retailer load forecasting affects the electricity tariff, thus how to develop innovative retailing strategies that manage the imbalances between supply and demand is an important problem concerned by electricity retailers [7]. The retailer

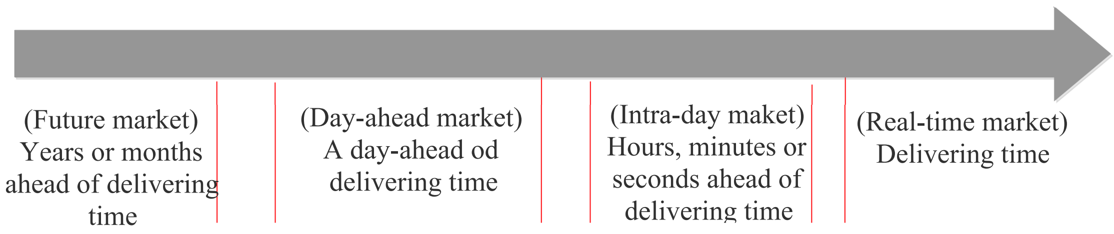


Figure 2.1. Sub-electricity markets as a function of the time when electricity is traded

is particularly concerned with load forecasting to mitigate excess electricity. Wholesale electricity markets provide platforms to large electricity consumers and electricity retailers to plan ahead, reserve electricity and correct load forecasting errors [36]. This provision is crucial and it takes place in four types of sub-electricity markets [37] shown in Figure 2.1.

Future electricity markets operate months or years ahead of electricity delivery rime by issuing bilateral contractual agreements to wholesale participants to deliver a specified amount of electricity at a certain price. Electricity retailers do not purchase electricity in future electricity markets, but only pay a reservation fee to protect the electricity generators. Future electricity markets contracts provide electricity retailers with affordable prices and enable the electricity generators and retailers to hedge against electricity price risks because of the high volatility RTPs. The significant role of forward markets was experienced during 2000-2001 by the California electricity market when it prohibited electricity retailers from signing bilateral future contracts [38]. The prohibition resulted in severe financial challenges due to high RTPs in California, while the electricity retailers in nearby states that experienced the same high RTPs were not affected because they based a small percentage of their electricity purchase on real-time pricing. The biggest drawback of forward markets is the high risk. Long term contracts with higher energy prices can be signed which can turn out to exorbitant compared to the real-time price, and contracts can forecast excessive electricity supply.

The day-ahead electricity markets are spot markets where wholesale market participants provide bids to buy and sell electricity for the following day using day-ahead prices. The key in day-ahead electricity markets is reaching a financial certainty such that the risks of incurring excess operational is minimized. Previous studies on day-ahead markets are divided into three categories, improving day-ahead electricity price forecasting, handling the uncertainties and risks, and scheduling supply or demand. Electricity retailers strongly rely on the prices in the spot market for economic profitability, hence the need to develop price forecasting models. Artificial neuronal networks (ANN) models developed in [39, 40] produced and compared different day-ahead electricity price forecast models. Uncertainty models developed in [41, 42, 43] calculated the required energy reserves using ANN by estimating forecasting errors of supply and demand by analysing the errors using dedicated stochastic and statistical procedures. Models developed in [44, 45, 46] demonstrated the optimal scheduling of distributed and hybrid energy resources which leads to the optimal decisions from the generation and demand units and showed that a reliable schedule increases their profits.

The intra day electricity markets are spot markets that provide platforms for market participants to reinforce and correct their bids an hour before electricity is delivered. In previous studies, the electricity generators and electricity consumers in intraday markets submitted their electricity bids, containing an amount of electricity and the time interval when the electricity is to be traded [47]. Transaction is approved when supply and demand match in the intra day electricity markets.

The real-time market is used by the wholesale market to balance electricity supply and demand in real-rime. The market operator constantly monitors the electricity supply and demand discrepancy of all the wholesale market participants. When any undesired discrepancy to undesired levels occurs, the market operator dispenses supply and demand balancing techniques to stabilize the electrical gid. Previous studies on real-time networks mainly focused on dispensing the cost of executing the balancing techniques is among participants who caused the imbalance [48].

Electricity consumers and prosumers in the electricity markets are the end-user agents of the electricity. Electricity prosumers are the consumers that also produce electricity. Consumers and prosumers aim to minimize their electricity cost. In previous studies, electricity consumers and prosumers have participated in electricity cost minimizing techniques as to minimize their electricity cost [49, 50]. Prosumers further sell the excess energy from the electricity generating sources to either the electrical grid in the peer-to-grid (P2G) mechanism or to their peers in the P2P energy sharing framework [21, 22]. Electricity consumers who do not generate their own electricity purchase their electricity from the electricity retailer, which means that many consumers, particularly in developing countries do not have a choice regarding their electricity suppliers. However, prosumers generate their own electricity and rely on the electricity retailers backup service only.

2.3 LOAD FORECASTING IN ELECTRICITY RETAIL MARKETS

Electricity retailers face the problem of consumer load forecasting in order of balancing the electricity in the retail market as required by the wholesale electricity market. Unlike the large electricity consumers that are to balance their individual electricity supply and demand, electricity retailers have an advantage to mitigate load volatility risks by aggregating multiple consumers and conducting their total load forecasting as a single unit. Load forecasting performed for multiple electricity consumers as a single unit results in load forecasting errors of single electricity consumers cancelling out, and thus results in lower load volatility risks. Using the electricity consumers' load pattern data from smart meters, electricity retailers are able to gain a better understanding of customer loads and mitigate high exposures to load volatility risks [8]. The accuracy degree of load forecasting affects the electricity retail tariff, hence developing novelty retailing strategies that manage the imbalances between electricity supply and demand is a crucial problem that electricity retailers are corned about [7]. Load forecasting provides a solution for the electricity retailer to increase their profits, however load forecasting is highly complex. The complexity of load forecasting is attributed to high variability of electrical load demand. Load demand is affected by various factors such as climate variations within a year, weather temperature, relative humidity, wind speed, dew point and social-economic factors such as income, education, employment, community safety, all make load forecasting a complex procedure [51]. Though complex, load forecasting is an essential part of the electricity retailers' planning and management process [52].

Studies show that load forecasting is performed over four load forecasting horizons, based on the electricity consumption, weather forecasts, economic forecasts and land-use changes namely; the very short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF) and long-term load forecasting (LTLF) [53].

The VSTLF is estimated a few minutes to an hour ahead of real-time electricity demand, and it is performed in the intraday electricity markets. Electricity markets require a 5-minute production schedule of the generators, such that the electricity generators notify the network operators of their maximum supply capacity in order to match it to the demand forecasts [51]. This prediction provided by VSTLF enables other market operators to respond to potential supply deficiencies by increasing either their generations or network capacity to meet the expected demand.

The STLF provides load forecasting over a day or week ahead, and it is the load forecasting technique performed in the day-ahead electricity markets. In the STLF, the level of the electricity consumers' economics and their building structures are relatively constant, however the atmospheric temperature can change enough for it to play a hand in the load demand between a few days. Studies on STLF have therefore predicted the load demand based on the forecasted temperature. The day-ahead market makes use of the short-term load forecasting (STLF) information for high accuracy load predictions [54]. To perform STLF in day-ahead retail markets, existing studies have favoured artificial neural network (ANN) to develop STLF algorithms [54]. ANN exhibit good non-linear curve fitting abilities by learning from experience to forecast values using some input data. ANN models are able to self organize, they learn quickly from adoption and they tolerate faults. These advantages make ANNs very attractive in problems of load forecasting [55]. This study considers a low-level ANN algorithm to illustrate the effectiveness of the research study. Similar day (SD) ANN model and day-ahead (DA) ANN model are examples of two low-level ANN models [55, 56, 57]. SD ANN searches historical data to find days which correlate with the day to be forecasted in terms of time and day of the week and weather characteristics. DA ANN fits the load demand of the previous day to the load demand of the day to be forecasted.

The MTLF provides load forecasts from 2 weeks to a year ahead of electricity delivery time, and it is performed in the future electricity markets. Studies utilize MTLF to ensure that security and capacity constraints are met in the medium term [51]. Temperature predictions are necessary in MTLF, however they have been found to be difficult. Studies show that simulated scenarios of temperatures based on the local temperature history have been used in the MTLF to successfully predict temperature. The electricity consumers' levels of economics are required in MTLF as well, because they affect the mid-term load consumption, while Land-use information are optional in MTLF [53].

The LTLF provides load forecasting between a year to 50 years ahead of electricity delivery and it is performed in the future electricity markets. The main purpose of LTLF is to identify needs for major generation planning and investment, since large electricity generating companies may take a decade to be constructed due to the challenging project requirements and the needs to design, finance and build them. In the LTLF, the building structure and the terrain of the electricity consumers has the potential to change dramatically and it is the major factor that affects the consumers' load. Studies on LTLF show that, a requirement on the information of land planning is vital to improve forecasting accuracy. The consumers' level of income and the atmospheric temperate is hard to predict, and such information is rarely available [53]. Studies simulate probable scenarios to predict them, This makes LTLF accuracy relatively low.

2.4 REGULATING ELECTRICITY IN ELECTRICITY RETAIL MARKETS

In order to meet the objective of the electricity retailers of maximizing their profits through electricity resale, studies show that the electricity retailers are to minimize the excess electricity from low demand periods and minimize deficit electricity supply during high demand periods [19]. The limited electricity reserve banks in an electrical system means that the electricity generated is to be consumed instantly and demand is to be met instantly as well, as to match electricity supply and demand. The instantaneous matching of supply and demand results in a reliable and secure operation of the electrical system [58]. An unreliable electrical system leads to electricity blackouts, incurs penalty costs for the electricity market participants, in addition to profit losses due to electricity dumping and unforecasted electricity electricity trading [59, 60].

Before electricity blackouts, an independent system operator (ISO) which is responsible for ensuring a continuous balance between supply and demand in the entire electricity transmission network, performs three control techniques in a sequential order namely; primary frequency control (PFC), secondary frequency control (SFC) and tertiary frequency control (TFC) [61]. PFC adjusts the power injected into the electrical grid by the generators and the power consumed by adjustable loads, by engaging and disengaging the speed controller of the generators to instantly restore the balance between generation power and load demand as to stabilize the frequency, before triggering the under or over frequency protection relays. The speed controllers automatically detect the frequency deviation every few seconds when it deviates from the nominal frequency to beyond a unacceptable frequencies. PFC is designed to counteract frequency variations following large load or generation outages. The demand side participates in PFC by making use of frequency sensitive loads and frequency sensitive relays that disconnect loads given frequency thresholds. PFC has a response time of seconds, and the electricity generators engaged to increase their output power because the system frequency has decreased cannot sustain the required output for long, and an alternative must replace them before they run out [62]. SFC steps in and adjusts the power injected into the electrical grid by the generators and maintains the balance between generation and load, essentially maintaining the frequency into a desirable range close to the nominal frequency, following an imbalance. Contrary to PFC which limits and stops frequency deviations with fast actuation, SFC slowly brings the frequency back to its nominal frequency. SFC is much slower than the PFC, with a typical time response of 10 to 15 minutes. It maintains the load and generation balance specific to an area where the imbalance occurred. SFC is not absolutely necessary and it is not performed in a smaller electricity markets, however necessary in large electricity markets as manual TFC technique will not stabilize the frequency fast enough. The main limitation SFC is the capability of generators to change the production [63]. Contrary to PFC and SFC, TFC requires manual re-dispatches of the electricity generators and loads by an operator after a severe frequency disturbance to restore the PFC and SFC, to regulate the consumers connected to the transmission network, and in cases where the SFC failed to stabilize the frequency, to bring the frequency back to ts nominal value. TFC has a response time of a few minutes [64]. The cost of executing the three mandatory techniques is shared between electricity market participants that did not comply with their contractual electricity supply. The electricity consumers and retailers that directly purchase electricity from the wholesale electricity market have little to no input on the contract bridge penalty costs.

The inability to balance electricity on the supply-side after TFC results in electricity blackouts. It has therefore been necessary to deregulate the electricity market and allow electricity market participants to participate in supply and demand balancing. Over the last three decades, a deregulation of the electricity market has been implemented and on the rise, and it has resulted in high electricity cost savings for the electricity consumers. Studies show that the participation of electricity retailers and consumers to reduces the costly contract bridging penalties, thereby minimizing their electricity costs [19]. Previous studies have developed and proposed a number of technologies for electricity retailers and consumers to match supply and demand, thereby securing the operation of the electrical system and minimizing their electricity cost. The peer-to-peer (P2P) energy sharing and implementing battery energy storage systems (BESSs) have particularly gained momentum due to their economic benefits to both and electricity retailers and consumers [19, 65].

2.4.1 Battery energy storage system

An increased penetration of distributed energy resources (DER) in the electrical system, provide an environment-friendly system with low carbon emissions and a sustainable future [66]. However, the DER such as photovoltaic electricity generation and wind electricity generation are based on natural conditions, making them highly intermittent electricity generation resources. The electricity retailers and ISO find it difficult to maintain electrical grid stability because of not only the random nature of load demand, but also the random nature of the DER. Studies show that incorporating BESS enhances the stability and regulates electricity [67]. Utilizing battery energy storage systems (BESS) on the demand-side show potential to minimize excess and deficit electricity, thereby significantly minimizing the electricity cost of the electricity consumers. The use of BESS to regulate electricity in the electricity market dates back to about 20 years ago [68]. BESSs alleviate load forecasting errors to regulate the electricity by absorbing excess electricity to supply electricity deficit, inject instantaneous electricity to the electrical grid and back up the conventional generation systems [15, 69]. A practical operation of a 100 MW BESS installed in the South of Australia indicates that BESSs are very well suited to regulate electricity in an electricity retail market due to their fast response [70]. The aim of BESS on the demand-side is to replace the existing electricity generators that are set aside as reserves to balance supply and demand. Studies show that BESS exhibit the ability to minimize the electrical system supply and demand fluctuations. BESS are therefore seen as the most viable tool to stabilize supply and demand.

BESS have a quick response and are a reliable technology because of their excellent ramp rate [68]. Studies show that BESSs respond quicker to load changes, have high energy efficiency of up to 95% which are favourable in enhancing the system stability. In 2017, BESS on the demand-side held 11 GWh of the total ESS worldwide and have a predicted growth rate of 100 GWh to 167 GWh in 2030 [10]. Due to the rise and benefits of BESS, BESS have gained popularity as measures for retailers to increase their profits and for consumers to reduce their electricity costs. Previous studies show that consumers implementing batteries can decrease their electricity expenditure by 40% [11], additionally consumer BESS can relieve the distribution grid by 20% of excess electricity by adopting a charging strategy [12]. By relieving the grid of excess electricity, consumers can make annual profits of $3000 [19, 71]. Studies show that electricity providers can make annual profit by using BESS high as $236-439 per KW in the United sates electricity market [68]. It is therefore evident that BESS do not only maximize their capacities with excess electricity to ensure a supply of loads during low-supply high-demand periods, but also improves the financial aspect of consumers [13].

To reduce the electricity cost of consumers using BESS, the electricity retailers in previous studies used electricity pricing models to regulate charging and discharging of electricity consumers BESS. By participating in BESS charging and discharging, a reliable and secure operation of the electricity network is established and consumers minimized their electricity costs [2]. Due to the great electricity cost saving potential of implementing BESSs, previous studies have proposed a number of BESS models. BESS models on the demand side have been implemented by three main types of consumers, electric vehicles (EVs), residential buildings and commercial buildings. EVs in [71, 72, 73, 74] were encouraged by dynamic pricing systems to provide supply and demand balancing, which results in a reliable electrical grid. The dynamic pricing systems regulated the charging and discharging EV BESSs, as a result minimizing the electricity cost of the EV consumers. Similarly, residential consumers in [19, 75, 76, 77] provided decentralized supply and demand balancing solutions on the demand side. The electricity retailers, aggregators and electricity coordinators encouraged the household consumers with smart pricing systems that will reduce their electricity cost, when they participate in BESS charging and discharging. The work in both consumer BESS models did not cater for consumers without BESS electricity, deficit electricity and a deficit electricity supplier. Not taking this issue into account increases the unreliability and instability of the electrical grid, consequently addressing this issue reduce the electricity cost of consumers and increases the reliability of the electrical grid. Studies on BESS charging and discharging have implemented the various models using various battery technologies discussed in the following section.

2.4.1.1 Battery technologies

The most common BESSs implemented by consumers on the demand-side are the lead acid batteries and the lithium-ion batteries [78]. Lead-acid batteries are a well proven safe technology that has been used for over a century, whereas lithium-ion batteries are a fairly new technology. Lead-acid are relatively more affordable compared to lithium-ion batteries, however, they need continuous maintenance and their lifespan is short. Lithium-ion batteries do not need maintenance and their lifespan is considerably long, however they have a high investment cost. Lead-acid batteries have low resistance to damage as they are damaged instantly if discharged too quickly or deeply below 50% of their State of Charge (SOC), whereas lithium-ion batteries are more resilient to irregular discharging and can be discharged quickly up to 85% of its SOC without any long term damage. Lithium-ion batteries have extremely high energy density, 25% the size and weight of an equivalent lead-acid battery. Lithium-ion batteries have low losses during charging and discharging up to only 8% resulting in very high round-trip efficiency, unlike lead-acid batteries which have charging losses of up to 20 % [79]. The electricity cost minimizing technique proposed in this study uses the lithium-ion battery technology for its high charging and discharging efficiencies.

2.4.2 Peer-to-peer (P2P) energy sharing

Studies show that trading electricity minimizes excess electricity. Over the last two decades, prosumers began trading the excess electricity from their renewable energy sources (RES) with the electrical grid in a peer-to-grid (P2G) energy sharing framework using a feed-in-tariff (FIT) [21, 80]. FIT schemes were on the rise in many countries worldwide for the purpose of backing up the electricity generating companies with various small-scale distributed energy resources (DERs) [81]. However, the rise in RESs which are sporadic in nature result in stochastic excess electricity which presents additional tasks to balance supply and demand in the already complex operation of the electrical grid. Existing studies show that for every 10% adoption of a RES, a balancing electricity between 2% and 4% is required [18]. For these reason, there has been a significant drop in the P2G electricity trading. The effects have been a drop in the electricity exporting prices, lower than those in the electricity retail market. The low attribute of electricity retail market prices encouraged self-consumption which is a measure of self-sufficiency. Studies show that consumers incorporating RES with an annual net zero energy use achieved self-sufficiency around 20-30% [20]. Over the years, research in the field of improving self-sufficiency gained popularity. A few studies proposed BESS demand-side management techniques. It is found that consumers can achieve a further 13%-24% of self-sufficiency when they incorporate a BESS of 0.5-1 kWh per installed kWp and a further 2%-15% when they implement DSM [20]. P2G, BESS and DSM are all based on improving a consumer's self-sufficiency and improving their electricity cost. Studies show that electricity consumers can achieve better self-sufficiency and electricity costs when they share their energy resources. In 2016, peer-to-peer (P2P) energy sharing was introduced to improve the drawback of P2G energy trading, BESS and DSM which focused on self [20, 82]. P2P energy sharing is the process through which electricity prosumers sell their excess electricity directly to their neighbours [19, 20]. An existing study shows that P2P energy sharing can minimize the electricity cost of a community by 30% in comparison to the conventional P2G energy sharing, and it can increases a consumer's annual self-consumption by 10-30%, and self-sufficiency by 20% [21]. P2P enegy sharing has shown to reduce individual consumer electricity cost, as P2P energy sharing in [83] show that consumers who would consume \$6.24 can minimize their electricity cost by \$3.59 to consume \$2.65 of electricity when they implement P2P energy sharing. Although P2P can provide significant reduced electricity costs, consumer electricity costs remain high, and the challenges to improve the P2P energy trading framework and engage more prosumers remains a topic of interest in research. This study tackles this challenge by proposing a system where P2P energy sharing participants trade BESS electricity, that results from excess electricity in the grid.

The operation of P2P energy sharing is typically managed by an energy service provider (ESC). In order to encourage P2P energy sharing participation, the ESC influences consumers with internal P2P electricity prices that minimize their total electricity cost [20, 22].

The ESC manages the P2P energy sharing operations based in three main platforms. 1) blockchain based which presents a detailed database containing the electricity sellers and buyers in the P2P energy sharing as well as the internal selling and buying prices. The ESC allows consumers the freedom to choose the source or destination of their elect city and to trade electricity directly with them. P2P energy sharing based on blockchain technology has been implemented and its effectiveness proved in the United states of America and Australia [84]. 2) Online matching platform allows electricity prosumers and consumers to purchase energy directly from the selling prosumers using an online platform. The online matching P2P energy sharing provides electricity consumers with lower transmission costs, which often result in electricity prices lower than the retail electricity prices. P2P energy sharing based on online matching has been implemented and its effectiveness proved in the United Kingdom and in the Netherlands [84]. 3) Battery storage based P2P energy sharing allows individual electricity consumers that incorporate BESS to store excess electricity from their RES and sell it to neighbouring electricity consumers in the electricity retail market when the neighbours have deficit electricity supply. Battery storage based P2P energy sharing has been implemented in the SonnenCommunity, where the BESS were sufficient to supply electricity amongst each other, and replaced the conventional electricity provider [84].

Studies have since proposed dynamic pricing systems that are economically greater for consumers than the feed-in-tariff [22]. The dynamic pricing system influences consumers to participate in the P2P energy sharing network and trade the energy resources amongst each other. The consumers are eager to minimize their electricity cost and hence participate in P2P energy sharing. The P2P electricity prices are bounded by the electricity import and export prices of a microgrid. The electricity price of importing electricity from neighbouring consumers is lower than importing electricity from the electrical grid, and exporting electricity to neighbouring prosumers returns higher profits than exporting electricity to the electrical grid [22]. P2P energy sharing allows prosumers employed with BESS to trade energy BESS energy, and the pricing principle to economically benefit prosumers is the same as P2P energy traded directly from RES.

The P2P electricity prices are formulated either by bill sharing mechanism (BSM), mid-market rate mechanism (MMRM) or by supply and demand ratio mechanism (SDRM) [85]. BSM totals all the electricity shared between the electrical grid and the prosumers in a microgrid to get one bill that it shares amongst the prosumers. P2P energy sharing is not billed in BSM and this results in significant electricity cost savings when the electricity load demand and electricity generation in the microgrid is matched [86]. The electricity bill can therefore either be a profit for all the P2P energy sharing participants when the overall microgrid exports electricity to the electrical grid or a loss or all the participants when the overall microgrid imports electricity from he electrical grid. Whether it is one of the other, the BSM shares the bill between consumers based on how much electricity each prosumer generates and consumed with respect to the entire microgrid. Because the BSM impacts the total costs of a microgrid, its drawback is that a single consumer would not the directly benefit from load shifting [87]. BSM also requires all he consumers to put the overall profits of the entire microgrid first before their individual gains, which is hard to manage, as often consumers are selfish and driven by instantaneous profits.

MMRM determines the P2P energy sharing price by the median price of the importing electricity from the grid and the median price of exporting to he grid based on the microgrid tne condition between total demand and generation. The MMRM is designed for microgrids with both consumers who buy electricity from the electrical grid and never sell excess electricity to the electrical grid, and prosumers who sell excess electricity to the electrical grid and may or may never buy electricity from the electrical grid [88]. Prosumers and consumers who are buying and selling in the P2P energy sharing are incentivized using the median price, and they equally share the energy saving, encouraging both of them to participate in the P2P market [89]. Unlike the BSM, the MMRM assists in load forecasting challenges for microgrids with consumers and prosumers, and it also has the potential to perform a consumer's load shifting in the interest of the overall microgrid.

SDRM also known as an auction based model allows prosumers to place the amount of energy they are offering to buy and sell as bids in the microgrid on a continuous basis [85]. The energy coordinator ensures that the demand and supply bids are matched at every period in time. The P2P energy sharing prices are determined by the amount of electricity that is available in the microgrid, such that when the bids to sell electricity are more than the bids to buy electricity, the internal buying and selling prices are low, similarly, when the bids to sell electricity are less than the bids to buy electricity, the internal buying and selling prices are high. Consumers are therefore incentivized to shift their loads to low internal buying price periods and prosumers are incentivized to shift electricity generation to high internal selling price periods [86, 90]. SDRM requires a high degree of consumer participation and their information. SDRM assumes that consumers, prosumers, retailers and electricity producers are all rational and therefore willing participants.

In a multi-agent framework, studies used the level of P2P energy sharing participation, the degree of balancing electricity in the microgrid, value tapping, equality, ability to flatten the power profile and self-sufficiency for different PV and EV charging penetration levels, conducted a detailed evaluation of the three P2P energy sharing price mechanisms, BSM, MMRM and SDRM [85, 91]. The results of the evaluation show that the SDRM presented the best outcomes for majority of the evaluating factors, followed by the MMRM, and the BSM presented the least overall outcome. The analysis show that both prosumers can minimize their electricity by implementing either the MMRM or the SDRM, however the MMRM presented lower equality in electricity revenue, additionally the MMRM only showed good performance with moderate PV penetration levels between 10% to 60% [85]. The study shows that SDRM is flexible, and the incorporation of a compensating variable can further improve the revenues of all P2P energy sharing participants. Overall, the SDRM outperforms the BSM and MMRM from an economic and technical point of view. Due to the high performance of SDRM, this study implements a SDR price mechanism for consumers in competition to achieve the low P2P energy sharing prices. The present literature studies on P2P energy sharing focused on tackling the excess electricity within a microgrid, but not the excess electricity from the electricity supplier. Not tackling this issue leads to electrical grid frequency will also increase the supply and demand instability of the electrical grid.

2.5 GAME THEORY

In chapter 1, game theory was identified as the optimization solver for consumers who are in competition for affordable electricity. This section presents a review of the current literature on game theory, particularly focusing on the application of game theory in battery charging games and P2P energy sharing. The concept of game theory is introduced followed by the different types of games that have been used in BESS are P2P energy sharing.

2.5.1 Overview of game theory

A game is generally defined as a competitive activity conducted according to rules with the participants who are decision makers in direct opposition to each other to win. Game theory is a theoretical framework that outlines situations in which decision makers interact according to a set of rules by using mathematical tools to analyse strategies to optimally make decisions of independent and competing players [92]. Each game consists of three essential objects; players, strategies and payoffs. The players are the individuals who carry out actions based on the information given in the game, and are always assumed to be rational decision makers, meaning that the players will always carry out the best action as per the players preference, among all the actions available to play [93]. The strategies are the set of actions available for the players to choose from. At every game unit step, each player is faced with a set of actions available to him/her from which he/she must choose a single element. The payoffs are the quantifiable benefits or losses that players get by playing a certain strategy. The payoff of each player depends on four elements; that player's action of preference, the other player's action of preference, the number of players and how frequent the game is played. When formulating a game, the payoff function is used to represent each players preference by associating each available action with different numeric values, where the most preferred action is assigned the highest number and the least preferred action is assigned the lowest number. A payoff function ultimately gives the payoff from each action. Game theory is mainly categorized into non-cooperative game theory and cooperative game theory.

2.5.2 Cooperative game theory

Cooperative game theory is concerned with descriptive games that specify the payoffs players will receive, however these descriptive games do not specify the process how the cooperation between players is formed. Cooperative game theory does not only analyse the payoffs from the actions of individual players, but it also analyses the externalities that these actions have on the overall payoff of the whole game. A successful cooperation between players is a factor that impacts the whole game. Cooperative games investigate how a cooperative structure can provide incentives to all the players as to act together as one entity in order to optimize their payoffs in the game. These cooperative structures in cooperative games can be formed either by peer communications or by a third party. In [94], a cooperative game was developed between consumers and an aggregator in which both parties cooperated as a single entity and maximized their benefits, that is the electricity retailer and consumers managed to maximize their profits and minimize their electricity costs, respectively.

2.5.3 Non-cooperative game theory

Non–cooperative game theory is concerned with analysing strategic decision-making processes. The concept of non-cooperative game theory is that the players are in competition with one another, and players make choices out of their own self-interest, because there is no cooperative structure. Each player in a non-cooperative game chooses the best strategy that renders them the best payoff without considering the strategy the other players choose or what is optimal outcome for the overall game. The disadvantage of non-cooperative games is that they can lead to suboptimal payoffs for all the players. Non-cooperative games can be a result of zero-sum interactions, whereby there can only be one winner, and the other player then must lose, and this forces each player to focus on maximizing his own payoff and disregarding the other players. Non-cooperative games can be a result of the inability to form cooperative structures due to social beliefs, geographical limitations or inadequate information. Non-cooperative games can also be a result of the incapacity to enforce cooperative rules, usually implemented by a third non-participating Non-cooperative games can either be static or dynamic. Static games allow players to choose their preferred action only once, either simultaneously or sequentially, whereas dynamic games allow players to choose their preferred action more than once because they have some information regarding the action chosen by other players. In [49], non-cooperative games provided optimal energy scheduling, as players undertook strategies motivated by pricing models in order to share energy between themselves and minimize their electricity costs by reaching a Nash equilibrium.

2.5.4 Nash equilibrium

Nash equilibrium is an optimal outcome of a non-cooperative game with a set of strategy choices from players, where one strategy belongs to one player, and no player can unilaterally improve his or her incentives by changing his or her strategy, given that the other players do not change their strategies. As players in game theory are assumed to be rational, all players stick to their chosen strategies [92, 95]. A game may have multiple Nash equilibria or none at all as explained in the main types of Nash equilibria presented in the next sessions.

2.5.4.1 Dominant Strategy

A dominant strategy is the strategy that always has the highest incentive than the other strategies in a set of strategies available to a player. Regardless of what strategies the other players choose in an outcome, a rational player will always choose to play his or her dominant strategy and will never choose to play a dominated strategy, because a dominant strategy is the optimal strategy unconditionally [96]. If all the players in a game have a strictly dominant strategy, then that game will only have one Nash equilibrium. An algorithm to find the dominant strategies in a game is determined using Table 2.1 which illustrates a 2-player game with a set of I strategies for player 1 and a set of J strategies for player 2 [93, 97]. The game thus has $I \times J$ outcomes and $2 \times I \times J$ payoffs. The payoff of player 1 playing strategy 1 when player 2 plays strategy 1 is given by $P_{i=1,j=1}$, similarly the payoff of player 2 playing strategy 1 when player 1 is playing strategy 1 is given by $P_{j=1,i=1}$.

Table 2.1. A payoff matrix for a 2-player game

strategies	**j=1**	**j=2**	**...**	**j=J**
i=1	$(P_{i=1,j=1}, P_{j=1,i=1})$	$(P_{i=1,j=2}, P_{j=2,i=1})$	...	$(P_{i=1,j=J}, P_{j=J,i=1})$
i=2	$(P_{i=2,j=1}, P_{j=1,i=2})$	$(P_{i=2,j=2}, P_{j=2,i=2})$	...	$(P_{i=2,j=J}, P_{j=J,i=2})$
...	...	...	...	...
i=I	$(P_{i=I,j=1}, P_{j=1,i=I})$	$(P_{i=I,j=2}, P_{j=1,i=2})$	...	$(P_{i=I,j=J}, P_{j=J,i=I})$

The strategies of player 1 are compared amongst each other to determine which strategy is dominant, similarly the strategies of player 2 are compared with amongst each other to determine which strategy is dominant in the algorithm in Table 2.2.

2.5.4.2 Best response

A best response Nash equilibrium is the optimal outcome of a game whereby each player plays their best response strategy. A player's best response is the strategy that generates the greatest payoff for him or her given what the other players are doing [98]. A strategy is a best response to, if and only if it is undominated. The game may have more than one Nash equilibrium, and each one of the Nash equilibria is a legitimate outcome of the game. With either of the Nash equilibria, no single player can increase their incentives by individually deviating to play a different strategy. If a game has multiple

Table 2.2. An algorithm to determine the dominant strategy

Algorithm(Dominant strategy)
for i=1:I
if $P_{i=i,j=1} > P_{i=i+1,j=1}$, $P_{i=i,j=2} > P_{i=i+1,j=2}$, ..., $P_{i=i,j=J} > P_{i=i+1,j=J}$
i $\rightarrow$ dominant strategy
i+1 strictly dominated strategy
end
for j=1:J
if $P_{j=j,i=1} > P_{j=j+1,i=1}$, $P_{j=j,i=2} > P_{j=j+1,i=2}$, ..., $P_{j=j,i=I} > P_{j=j+1,i=I}$
j $\rightarrow$ dominant strategy
j+1 strictly dominated strategy
end

Nash equilibria, it should be accompanied by a decisive measure to guide the players on which Nash equilibria will be selected. Studies on best response with multiple Nash equilibria have been concerned with equilibrium refinements in an attempt to determine the best Nash equilibria without leading players into a coalition. The algorithm in Table 2.3 shows the procedure followed to obtain the best response strategy [93, 97].

Table 2.3. An algorithm to determine the best response

Algorithm(Best response)
for i=1:I
best response(j,i) =max($P_{j=1,i=i}$, $P_{j=2,i=i}$,..., $P_{j=J,i=i}$)
end
for j=1:J
best response(i,j) = max($P_{i=1,j=j}$, $P_{i=2,j=j}$,..., $P_{i=I,j=j}$)
end

2.5.4.3 Pure-strategy Nash equilibrium

Pure-strategy Nash equilibrium is the state of a game when every player plays one specific strategy with a probability of one, called a pure strategy and the other strategies with a a probability of zero. A pure strategy provides a definitive on which strategy a player will play in a game [93, 97]. A game is in a Nash equilibrium if all players are playing their best response strategies, as illustrated in the algorithm in Table 2.4.

Table 2.4. An algorithm to determine the pure-strategy Nash equilibrium

Algorithm(Pure-strategy Nash equilibrium)
$c_{i,j} = 0$ (Nash equilibrium when this equals 2)
for i=1:I
best response(j,i) =max($P_{j=1,i=i}$, $P_{j=2,i=i}$,..., $P_{j=J,i=i}$)
$c_{i,j} = c_{i,j} + 1$
end
for j=1:J
best response(i, j) = max($P_{i=1,j=j}$, $P_{i=2,j=j}$,..., $P_{i=I,j=j}$)
$c_{i,j} = c_{i,j} + 1$
end
Nash equilibrium $\rightarrow c_{i,j} = 2$

Table 2.5. An algorithm to determine the mixed-strategy Nash equilibrium

Algorithm(Mixed-strategy Nash equilibrium)
for j=1:J
$EU_{1,j}$= a $\times P_{j=j,i=1}$ + b $\times P_{j=j,i=2}$ + ...+(1-a-b) $\times P_{j=j,i=I}$
end
solve unknown variables (a.b)
for i=1:I
$EU_{1,j}$ = c $\times P_{i=i,i=1}$ + d $\times P_{i=i,i=2}$ + ...+(1-c-d) $\times P_{i=i,i=I}$
end
solve unknown variables (c,d)

2.5.4.4 Mixed-strategy Nash equilibrium

A mixed-strategy Nash equilibrium is an outcome of a game whereby at least one player is playing a strategy that has been selected through randomization, determined in games without pure strategy Nash equilibria [93, 97]. A mixed strategy of player 1 in the given example above is played with a probability. Hence, the only case where player 2 could possibly randomize between her strategies is if both strategies give her the same payoff, that is, if she is indifferent between playing her strategies. Hence, player 2 randomly plays either strategy without losing payoff. The algorithm to determine the mixed strategy Nash equilibrium in Table 2.5 involves setting the payoffs for a player's two pure strategies equal to each other and solving for the mixed strategy of the other player [93, 97].

2.6 CONCLUSION

This study contributes to the field on handling risks and uncertainties in a day-ahead retail market. Using electricity consumers' smart meters, the DA ANN model has been selected for this study to predict the load profile in the day ahead electricity retail market because of its simplicity. Load forecasting in electricity markets is the approach to a reliable and cost minimizing for both the retailer and consumers. BESS and P2P energy sharing have been selected as techniques to balance electricity in the retail market, because of the benefits reviewed. For the P2P energy sharing, the SDRM has been selected to determine the framework of sharing energy amongst the consumers. Due to the high energy density of lithium-ion batteries over lead acid batteries, lithium-ion batteries have been selected as the BESS employed at consumers premises.

CHAPTER 3 BUSINESS MODEL FOR THE ELECTRICITY RETAILER

3.1 CHAPTER OVERVIEW

This chapter presents an electricity regulation system for an electricity retail market. The aim of the electricity regulation system is to maximize the profits of the electricity retailer and minimize the electricity costs of the electricity consumers. A non-linear optimization model is formulated to maximize the profit of the electricity retailer and minimize the electricity cost of the consumers savings. The optimization model is implemented by a game theoretical approach which minimizes the excess and deficit electricity in order to meet the objective of the electricity regulation system.

3.2 INTRODUCTION

Electricity retailers purchase electricity from the electricity wholesale market through a combination of long-term or short-term contracts with the electricity generation entities, based on LTLF, MTLF, STLF and VSTLF. The degree of accuracy from load forecasting directly affects the profits of the electricity retailer and the electricity costs of the electricity consumers. Unmanaged excess electricity is wasted and results in economical losses for the electricity retailer. Unmanaged deficit electricity requires purchasing unforecasted electricity from the electricity wholesale market. Electricity wholesale market prices use the RTP mechanism, which varies dramatically on an hourly basis, presenting a price risk which also results in economical losses for the electricity. It is hence crucial for electricity retailers to regulate both excess and deficit electricity. The economic status directly affects the electricity retail prices. As electricity retailers are in competition with each other for electricity consumers, developing techniques to minimize the electrify cost of the consumers is paramount.

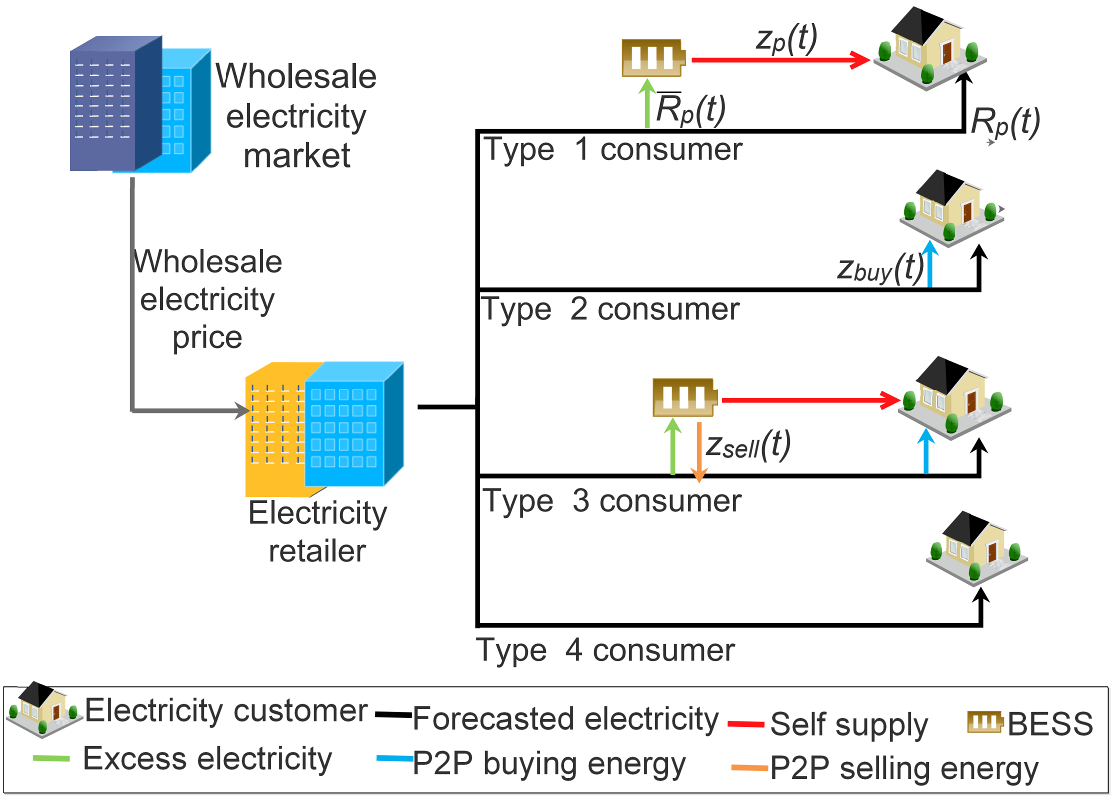


Figure 3.1. Schematic layout of the structure for the proposed electricity market

3.3 ELECTRICITY REGULATION SYSTEM MODEL PROBLEM

It is anticipated that many electricity retailers in future electricity market are small business owners. They have the opportunity to buy electricity from the wholesale market and then resell it to the their customers. According to different financial capabilities, these electricity retailers can expand their business scope by building their own renewable power generation or establish different types of energy storage systems. However, at the early business development stage, these retailers do not have sufficiency budget to build their own power plants with energy storage systems.

In this study, we consider a business case of an electricity retailer as a small business owner, which can be briefly illustrated in Figure 3.1. The retailer's major business scope is to buy electricity from the wholesale market at a wholesale price and then resell it to the associated customers at a retail price TOU_t, which is always higher than the wholesale price. It is always a challenging process for the retailer to decide the retail price. For instance, he cannot price it too low to lose benefit and he can neither price it too high to lose customers. The retailer's other challenge is to decide the amount of electricity to buy from the wholesale market. If he buys too much power, then the supply is greater than the customer's total demand. In this case, the excessive power will be wasted due to lack of battery storage. If he buys less power, then the supply cannot meet the customers total demand. In this scenario, the retailer has to buy additional power from the wholesale market at an extremely high price. For the retailer's normal operation, he buys the amount of electricity according to the forecasted total customer demand. However, there is always a load forecasting error which leads to an unavoidable mismatch between the supply and demand.

Under these circumstances, this electricity retailer always aims to maximise his total profit. Since he cannot afford battery energy storage systems on his own, he encourages the customers to install their own battery. The batteries enable the retailer and the customers in the community to establish a win-win business model. Firstly, when the retailer buys and supplies excessive electricity, the customers can charge their batteries at a lower price, ε_t^{buy} than normal retailer price. Secondly, when the retailer fails to supply sufficient power against the total power demand, the customers are allowed to trade the energy stored in their batteries to other peer consumers at an internal P2P buying price, z_t^{buy} and an internal P2P selling price, z_t^{sell}. We name the two scenarios battery charging mode and P2P energy sharing mode. However, the retailer cannot force each customer to buy a battery. Thus the consumers are naturally classified into four categories, namely 1) customers who have batteries and join the charging mode but do not participate in the P2P energy sharing mode; 2) customers who do not have batteries but are willing to buy electricity from the peer consumers; 3) customers who have batteries and join both the charging mode and the P2P energy sharing mode; and 4) customers who do not have batteries and are not willing to buy electricity from the peer consumers. For easier description, we name the four categories of customers Types 1-4 consumers, and their typical configuration characteristics are given in Table 3.1.

Table 3.1. Types of customers

Description	Battery charging mode	P2P sharing mode
Type 1	Yes	No
Type 2	No	Yes
Type 3	Yes	Yes
Type 4	No	No

With the proposed two battery operation schemes, the power mismatch between the supply and demand can be minimised. Hence the retailer finance losses suffered from the power mismatch are alleviated.

In the meantime, the customers are able to buy electricity at lower price in both the battery charing and P2P energy sharing modes.

The proposal sounds attractive to both the retailer and the customers for such a win-win business model. However, the associated technical challenges also arise in the following aspects.

1. The price structures for both the battery charging and the P2P energy sharing modes must be developed.
2. Optimal sizes of the batteries must be determined for the customers.
3. Each customers battery operation in terms of their power flow profile must be identified.
4. Financial impact of the proposal must be calculated and evaluated.

This study will focus on solving such technical challenges. To facilitate the problem formulation process, we made the following assumptions.

1. The electricity retail market applies a day-ahead price mechanism. More precisely, the retailer announces an hourly electricity price for the next 24 hours one day ahead.
2. The amount of electricity purchased by the electricity retailer from the wholesale market is determined by the average daily electricity consumption.

The retailer is interested in finding out which type of customer presented in Table 3.1 will alleviate the most excess snd deficit powers to achieve the lowest energy costs, and consequently provide the retailer with the most profits. To do this, the retailer will calculate and compare the energy costs of the four types of consumers. Energy cost, besides the price of energy, is affected by the excess and deficit powers of the retailer and the load profile of the consumers. To accurately compare the consumer energy costs, the retailer will assume that a customer with similar load profile exists for each type of consumer, and that each type of consumer experiences the same retailer excess and deficit power. For these reason, the mathematical formulations in the following sections will only be those of Type 3 consumers $i = 1, 2, ..., I$ because they encompass both battery charging mode and P2P energy sharing mode. The formulations for Type 1 consumers $g = 1, 2, ..., G$ are the same as those of Type 3 consumers, but without the P2P energy sharing mode, and the formulations for Type 2 consumers $h = 1, 2, ..., H$ are the same as those of Type 3 consumers, but without the batteries aspect.

The formulations for Type 4 consumers $j = 1,2,...,J$ neither include batteries nor P2P energy sharing mode.

3.4 ELECTRICITY RETAIL MARKET REGULATION SUB-SYSTEMS

This section presents the electricity price models utilized by the electricity retailer to regulate the consumer BESS charging and discharging.

3.4.1 Load demand for an electricity consumer

Each electricity consumer i comprise of $n = 1,2,3,...,N$ electrical appliances. If the electrical appliance n for consumer i has a real-time demand of $P(i_j,n,t)$ (kW) at time t, the real-time demand, $P(i_j,t)$ (kW) for consumer i at time t is given by:

$$P(i_j,t) = \sum_{n=1}^{N} P(i_j,n,t). \tag{3.1}$$

The total load demand P_i (kW) for consumer i over the period T is given by;

$$P(i_j) = \sum_{t=1}^{T} P(i_j,t). \tag{3.2}$$

3.4.1.1 Load forecasting model

Load forecasting is an essential part of the electricity retail market's planning and management process. It is the technique used to predict the amount of electricity presented to the electricity generating companies to be generated. The smart meters for the consumers in this study each use the DA STLF algorithm that considers the real-time load demand, $P(i_j,t)$ (kW), from the previous day to be the forecasted load demand, $\hat{P}(i_j,t)$ (kW), for consumer day-ahead. The electricity retailer aims to only supply forecasted electricity.

In the following subsections, the proposed business model is formulated into two non-cooperative games in terms of the battery charging game and the P2P energy sharing game.

3.4.2 Battery charging mode

In a base case scenario when there are no ESS available in the electricity retail market and supply from the retailer is greater than the real-time demand, the electricity retailer suffers from wasting of surplus electricity. Now, Type 1 and Type 3 consumers have installed their BESS. They also grant permissions to the retailer to charge their batteries when the supply is temporarily greater than the real-time power demand. The battery energy enables both self-supplying and trading energy to other consumers when the supply from the retailer is less than the real-time power demand in the community. The price for the surplus electricity, $\bar{R}_p(t)$, is adjusted according to [19], which is lower than the TOU tariff to encourage the consumers to charge their batteries.

$$\bar{R}_p(t) = R_p(t) - k \cdot P_e(t) \cdot \Delta t, \text{ for } P_e(t) > 0. \tag{3.3}$$

The excess electricity at time t, $P_e(t)$ is given by

$$P_e(t) = \sum_{j=1}^{4} \sum_{i_j}^{I_j} (\hat{P}(i_j,t) - P(i_j,t)). \tag{3.4}$$

The consumers compete for the excess power in a Nash equilibrium game because excess power is usually limited.

The battery charging mode is executed by the electricity retailer only when $P_e(t) > 0$. When $P_e(t) = 0$, the market is perfectly regulated, and when $P_e(t) < 0$, the electricity retailer experiences deficit supply, such that the battery energy can be used either for self-supplying mode or P2P energy sharing.

3.4.3 Equivalent electricity price for battery self-supply

Type 1 and Type 3 consumers can supply their loads by BESS installed when the retailor's supply falls short. Under such a circumstance, the equivalent electricity price $z_p(t)$ is determined by the expenditure in charging their BESSs and is mathematically calculated by

$$z_p(t) = \frac{\sum_{j\in\{1,3\}} \sum_{i_j=1}^{I_j} z_b(i_j,t)}{\sum_{j\in\{1,3\}} \sum_{i_j=1}^{I_j} E_b(i_j,t)}, \tag{3.5}$$

where

$$z_b(i_j,t+1) = z_b(i_j,t) + \Delta t[P_b^c(i_j,t)\bar{R}_p(t) - P_{sell}(i_j,t)z_{sell}(t)].$$

3.4.4 P2P energy sharing mode

P2P energy sharing mode is operated when two conditions are met: 1) the consumers in the electricity retail market demand more electricity than what the electricity retailer forecasted in the day-ahead market; and 2) Type 2 consumers are unable to supply their deficit supply while Type 3 consumers have leftover energy in their BESSs after supplying their own power deficit. The consumers with BESS energy and no deficit supply operate as electricity sellers. The electricity retailer operates as the ESC, facilitating the P2P energy sharing processes, i.e discharging consumer BESS, supplying deficit supply and regulating electricity costs. The consumers who sign a bilateral agreement with the retailer, are willing participants of P2P energy sharing. Under the P2P energy sharing mode, energy is traded among consumers based on an internal selling rate, $z_{sell}(t)$ (c/kWh), and bought using an internal buying rate, $z_{buy}(t)$ (c/kWh). In this study, the internal prices have two fundamental principles, 1) the internal prices are upper bounded by the energy rate of purchasing unforecasted/emergency electricity from the retailer, $R_p^u(t)$ (c/kWh), and are lower bounded by the equivalent BESS energy price $z_p(t)$ (c/kWh) as shown in Figure 3.2. This motivates consumers with deficit supply to purchase electricity from neighbouring consumers with BESS energy before purchasing emergency electricity from the retailer and ensures that consumers with BESS energy benefit economically from selling. 2) The internal prices are a function of supply and demand ratio (SDR), which is the ratio of how much electricity the consumers are selling to how much electricity consumers require to meet their deficit supply.

$$SDR(t) = \frac{\sum_{i_3=1}^{I_3} P_b(i_3,t)}{\sum_{i_2=1}^{I_2} P_d(i_2,t)}. \tag{3.6}$$

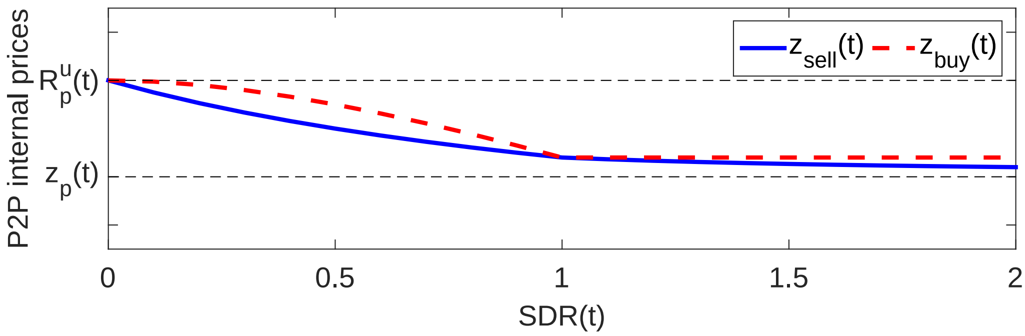


Figure 3.2. The internal pricing with a compensation variable as a function of SDR based for consumers in a P2P energy sharing retail market

The P2P selling and buying prices are adopted from [21, 22] and given in the following.

$$z_{sell}(t) = \begin{cases} \dfrac{(z_p(t)+\lambda)R_p^u(t)}{(R_p^u(t)-z_p(t)-\lambda)SDR(t)+z_p(t)+\lambda}, & 0 \leq SDR(t) \leq 1, \\ z_p(t)+\dfrac{\lambda}{SDR(t)}, & SDR(t) > 1, \end{cases} \tag{3.7}$$

$$z_{buy}(t) = \begin{cases} z_{sell}(t)SDR(t)+R_p^u(t)(1-SDR(t)), & 0 \leq SDR(t) \leq 1, \\ z_p(t)+\lambda, & SDR(t) > 1. \end{cases} \tag{3.8}$$

In Equations (3.7) and (3.8), λ is a compensation variable that encourages Type 3 consumers to participate in P2P selling. Without λ, consumers selling power in P2P may have negative benefits from P2P energy trading.

3.4.5 Battery energy storage system

For Type 1 and Type 3 consumers, the energy stored a lithium-ion battery takes into account the charging rate at time t, $b_{i,t}^c$, the discharging rate at time t, $b_{i,t}^d$, the sampling interval Δt=1 hour, the charging efficiency η^c and discharging efficiency η^d, given as

$$\begin{aligned} E_b(i_j,t+1) =& E_b(i_j,t)+\eta_c P_b^c(i_j,t)x_b^c(i_j,t)\Delta t \\ &- \frac{P_b^d(i_j,t)}{\eta_d}x_b^d(i_j,t)\Delta t. \end{aligned} \tag{3.9}$$

To ensure that charging and discharging do not happen at the same time, the following must be satisfied

$$x_b^c(i_j,t)+x_b^d(i_j,t)\leq 1 \text{ for } x_b^c(i_j,t) \text{ and } x_b^d(i_j,t)\in\{0,1\}. \tag{3.10}$$

Additionally, the energy stored in BESSs are bounded by their respective full capacities determined according to the IEEE lithium-ion battery sizing standard given by [99]

$$E_b^{MAX}(i_j)=2.18\Delta t\sum_{t=1}^{T}P_{i_j}(t) \text{ for } j\in\{1,3\}. \tag{3.11}$$

As a result, the following constraint applies:

$$0.5E_b^{MAX}(i_j)\leq E_b(i_j,t)\leq E_b^{MAX}(i_j) \text{ for } \forall i,j,t. \tag{3.12}$$

The cost of the battery is given by

$$C_{i,t}^b=b_i^{MAX}\cdot r^b. \tag{3.13}$$

where r^b represents the cost per kWh for Type 1 and Type 3 consumers' batteries.

3.5 GAME THEORETICAL MODELLING

The retailer tries to maximize its profit in the day-ahead market given by

$$J_r=\begin{cases}\sum_{t=1}^{T}\Big(\hat{P}_T(t)(R_p(t)-R_g(t))+P_e(t)\bar{R}_p(t)\Big) & \text{if } P_e(t)\geq 0,\\ \sum_{t=1}^{T}\Big(\hat{P}_T(t)(R_p(t)-R_g(t))+ & \\ \quad (P_e(t)-P_{b,T}^d(t))(R_p^u(t)-R_g^u(t))\Big) & \text{if } P_e(t)<0,\end{cases} \tag{3.14}$$

where

$$\hat{P}_T(t)=\sum_{j=1}^{4}\sum_{i_j=1}^{I_j}\hat{P}(i_j,t),$$

and

$$P_{b,T}^d(t)=\sum_{j=1}^{4}\sum_{i_j=1}^{I_j}P_b^d(i_j,t).$$

The retail needs to solve this problem repeatedly in a day-ahead fashion. The retailer's profit depends on the consumers optimal action strategies in the battery charging and P2P energy sharing game.

In the following, the battery charing and P2P energy sharing of consumers are formulated and solved following a game theory approach.

According to the oversupply and undersupply status, the consumers play two different games namely the battery charging game and the P2P energy sharing game, respectively. It is assumed that in both games, the consumers are rational and strategic decision makers who aim to minimze their costs. The consumers realize their payoffs at a Nash equilibrium.

3.5.1 Battery charging game

The battery charging game is played by the Type 1 and Type 3 consumers. These consumers enter an electricity competition to maximize their battery capacity by strategizing their charging patterns basing on the electricity surplus, the charging rate and their batteries' capacity.

For this game, the strategies of each consumer is whether to charge the battery or not. The strategy of consumer i_j is $x_b^c(i_j,t)$ and the strategy of of all consumers other than the consumer i_j is $x_b^c(-i_j,t)$.

The cost function in the charging game for Type 1 and Type 3 consumers are given in Equations (3.15) and (3.16).

$$\gamma_1(x_b^c(i_1,t),x_b^c(-i_1,t)) = \sum_{t=1}^{T}\Big(P(i_1,t)R_p(t)+R_p^u(t)P_d(i_1,t) \\ +x_b^d(i_1,t)z_p(t)P_b^d(i_1,t)+x_b^c(i_1,t)\bar{R}_p(t)P_b^c(i_1,t)\Big) \tag{3.15}$$

$$\gamma_1(x_b^c(i_3,t),x_b^c(-i_3,t)) = \sum_{t=1}^{T}\Big(P(i_3,t)R_p(t)+R_p^u(t)P_d(i_3,t) \\ +x_b^c(i_1,t)\bar{R}_p(t)P_b^c(i_3,t)+x_{buy}(i_3,t)z_{buy}(t)P_{buy}(i_3,t) \\ -x_{sell}(i_3,t)z_{sell}(t)P_{sell}(i_3,t)\Big) \tag{3.16}$$

The number of consumers that can charge is given by $n_t = \frac{P_e(t)}{P_b^c(i_j,t)}$ at time t. If $P_e(t)$ is a multiple of $P_b^c(i_j,t)$, then n_t is a set of positive integers. The Nash equilibrium algorithm in Table 3.2 determines the consumers' optimal BESS charging or idling behaviours.

Table 3.2. Pure-strategy Nash equilibrium algorithm

Algorithm 1 - Pure-strategy Nash equilibrium
initialize outcome c_{i_j}=0
initialize player $i_j = 1$
while $i_j \neq I_j$
for $i^- : I_j^-$ (all other players other than player i)
for $x = x_b^c(i_1,t)$ (the strategies for player i_j)
best response $(x_b^c(i_1,t), x_b^c(-i_1,t))$ =
$\max(\gamma_1(x_b^c(i_1,t), x_b^c(-i_1,t)), \gamma_1(x_b^c(i_3,t), x_b^c(-i_3,t)))$
increment outcome c_{i_j} with best response
end
end
increment i_j
end
Nash equilibria $\rightarrow$ outcome of c_{i_j}

The algorithm in Table 3.2 determines the pure strategy Nash equilibrium of an $I_j^- th$ player game where each player has X strategies. Each player determines the best strategy to play given what other players are playing. The algorithm is manually coded in MATLAB, in order to find the Nash equilibrium at every time t.

3.5.2 P2P energy sharing game

When the power supply from the retailer cannot meet the total demand from the consumers, the consumers in the community enters a P2P energy sharing game. The players of the P2P energy sharing are Type 2 and Type 3 consumers. In this game, consumers who are unable to satisfy their own loads compete to purchase electricity while consumers with surplus power in their batteries compete to sell electricity. When there are no sellers, consumers planning to purchase P2P electricity remain idle. Similarly consumers who wish to sell electricity remain idle when there are no buyers. Therefore, at time t, consumer i_j has three strategic actions available, buying, selling or idle. To simplify notations, the following variable is introduced:

$$v(i_j,t) = \begin{cases} 1, & \text{buying: } x_{buy}(i_j,t)) = 1,\ x_{sell}(i_j,t)) = 0, \\ -1, & \text{selling: } x_{buy}(i_j,t)) = 0,\ x_{sell}(i_j,t)) = 1, \\ 0, & \text{idel: } x_{buy}(i_j,t)) = 0,\ x_{sell}(i_j,t)) = 0. \end{cases} \tag{3.17}$$

Cost of a Type 2 consumer i_2 in the P2P sharing game is:

$$\begin{aligned} \gamma_2(v(i_2,t),v(-i_2,t)) = \sum_{t=1}^{T} \Big(& P(i_2,t)R_p(t) + R_p^u(t)P_d(i_2,t) \\ & + x_b^c(i_1,t)\bar{R}_p(t)P_b^c(i_2,t) + x_{buy}(i_2,t)z_{buy}(t)P_{buy}(i_2,t) \Big). \end{aligned} \tag{3.18}$$

For a Type 3 consumer, the cost function is:

$$\begin{aligned} & \gamma_2(v(-i_3,t),v(-i_3,t)) = \\ & \sum_{t=1}^{T} \Big(P(i_3,t)R_p(t) + x_b^c(i_1,t)\bar{R}_p(t)P_b^c(i_3,t) + R_p^u(t)P_d(i_3,t) \\ & + x_{buy}(i_3,t)z_{buy}(t)P_{buy}(i_3,t) - x_{sell}(i_3,t)z_{sell}(t)P_{sell}(i_3,t) \Big). \end{aligned} \tag{3.19}$$

The Nash equilibrium algorithm in Table 3.2 determines the consumers' selling, buying or idling actions.

It is noted that Type 4 consumers' have no control of their electricity costs showing in (3.20) because they do not participate in either battery charing nor P2P energy sharing game.

$$J_c(i_4) = \sum_{t=1}^{T} \Big(P(i_4,t)R_p(t) + R_p^u(t)P_d(i_4,t) \Big). \tag{3.20}$$

3.6 CASE STUDY

The effectiveness of the proposed business model will be tested under a case study. A small community with 12 consumers living together is considered. As introduced before, these consumers are naturally classified into four types according to their availability of batteries and willingness to participate in the battery charging and the P2P energy sharing schemes. In the case study, we assume the 12 consumers are evenly distributed in each consumer group. Hence there are 3 consumers of each type. In addition, the 3 consumers of each type have different daily load profiles. These load profiles are randomly selected from a pool of 300 household load profiles that were recorded in Australia from 1 July 2012 to 1 July 2013 [100]. In addition, for comparison purposes, we assume that the energy consumption patters of consumers of each type are identical. That is, the 3 Type 1 consumers exhibit the same load profiles as the 3 Type 2 consumers, but the load profiles for each consumer of the same type is different. Table 3.3 lists all the initial values used in the simulation.

Table 3.3. Initial values used in the simulation

T	24 h
Δt	1 h
$E_b(1_1,1)$	0.2 kWh
$E_b(2_1,1)$	1.1 kWh
$E_b(3_1,1)$	1.3 kWh
k	1.2
R_g	A\$3.79 cent/kWh
R_g^u	A\$3.90 cent/kWh

CHAPTER 4 RESULTS AND ANALYSIS

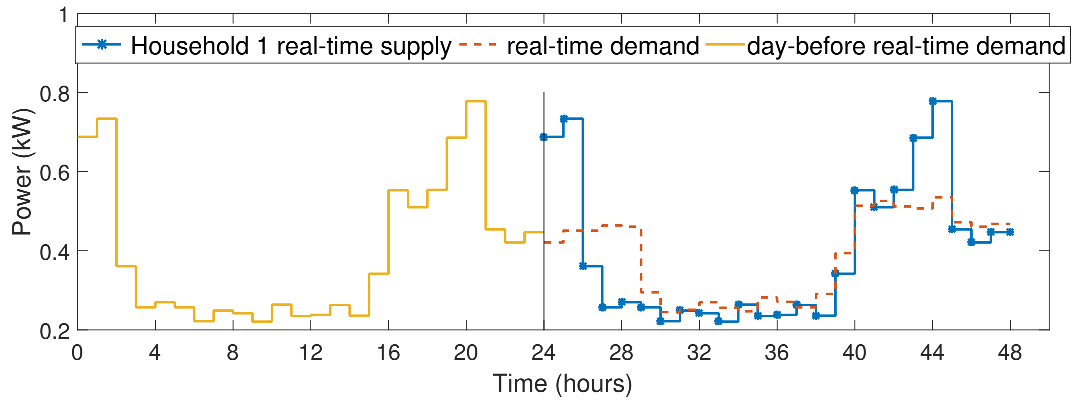
4.1 CHAPTER OVERVIEW

This chapter presents the results for the four types of consumers formulated in Section 1.3. The main objective of this chapter is to assess the effects of the pricing models formulated in Chapter 3 on the energy cost of the consumers and the electricity retailer profit. The electricity consumers aim to minimize their energy costs while the electricity retailer seeks to maximize the profits from electricity resale.

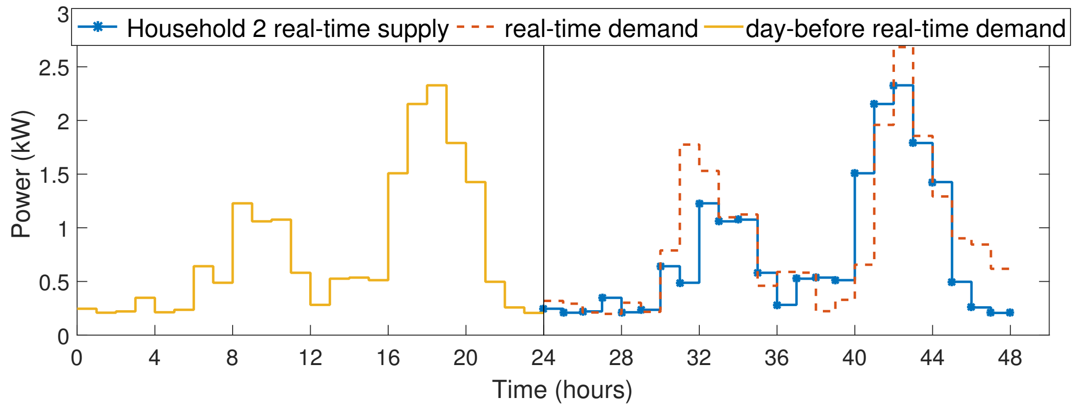
4.2 FORECASTED LOAD DEMAND

The case study shows that there are twelve household customers in the small-scale electricity retail market, of which a set of three household load profiles exist for each type of consumer. As the retailer individually analyses each type of consumer, the predicted load demand that is the electricity supply at each time t for the electricity delivery day determined using the day-ahead forecasting model for one type of consumer is shown in Figure 4.1. It is seen that the real-time demand for the first 24 hours in the figure for household 1, household 2 and household 3, illustrating the day before delivery is equivalent to the electricity supply for the delivery day, illustrated as the last 24-hours of the 48 hours.

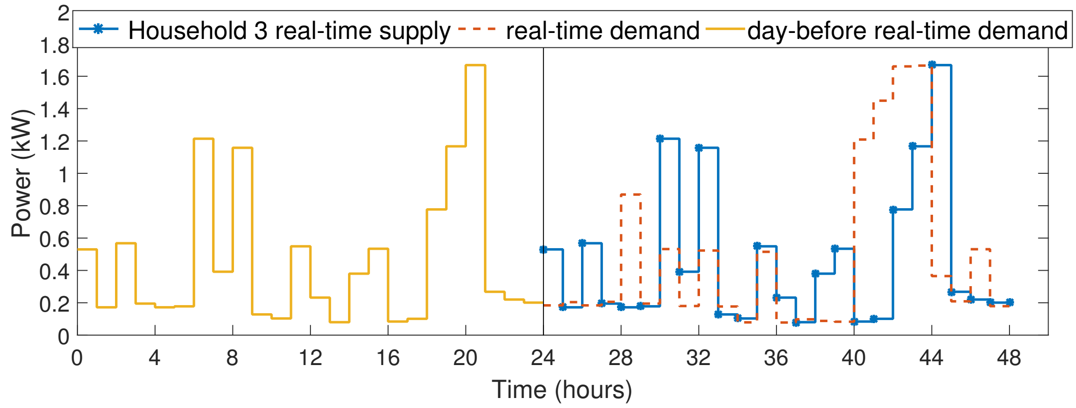
The electricity retailer aggregates the planned electricity supply for the three load profiles at each hour for 24-hours as well as the real-time demand for the three load profiles at each hour for 24-hours during the electricity day, as shown in Figure 4.2.



(a)



(b)



(c)

Figure 4.1. Forecasted and real-time demand for (a) load profile 1 (b) load profile 2 and (c) load profile 3

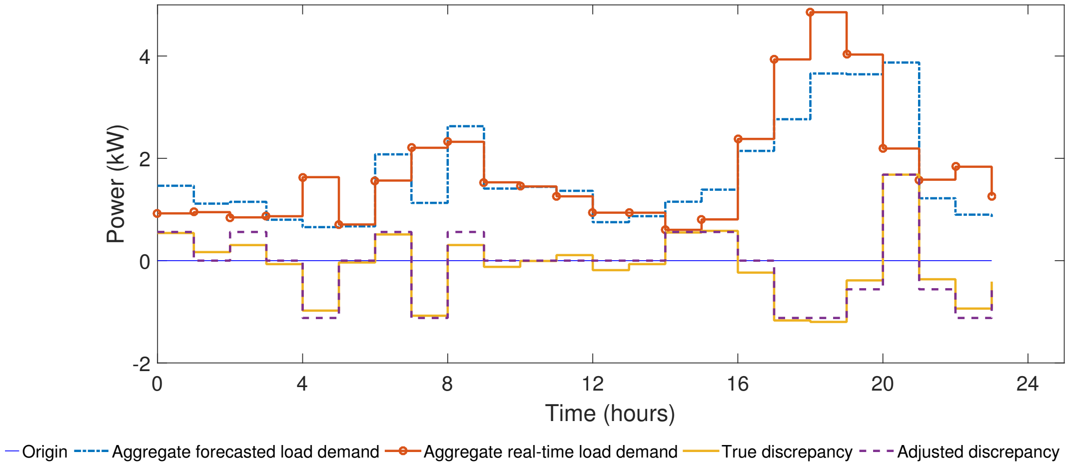


Figure 4.2. Aggregate electricity supply and demand with the true and adjusted discrepancy

The aggregated forecasted load profiles are also plotted against the real-time aggregated load demand as shown in Figure 4.2. The electricity retailer takes the highest absolute discrepancy value 1.68 kWh and divides it by the total number of households (three) to obtain the charging power of 0.56 kW. Each value of $P_e(t)$ is rounded off to the nearest charging power of 0.56 kW and $P_e(t)$ is adjusted such that the charging power is a multiple of the adjusted$P_e(t)$, and the number of consumers that can charge their BESS with surplus electricity is a whole number, as shown in Figure 4.2. When the adjusted discrepancy is greater than 0, $\bar{R}_p(t)$ is lower than $R_p(t)$ as shown in Figure 4.3 and the retailer supplies a number of household BESS with the surplus electricity, depending on the amount of discrepancy. The battery capacities of household 1, household 2 and household 3 are 19.18 kWh, 42.41 kWh and 23.17 kWh, respectively. The three Type 1 households and the three Type 3 consumers are all eager to charge as much as energy as they can at a lower electricity price $\bar{R}_p(t)$, as it gives them an opportunity to self-supply with lower electricity prices when the adjusted discrepancy is less than 0, and $\bar{R}_p(t)$ is greater than $R_p(t)$. The Australian summer TOU tariff is applied as shown in Figure 4.3.

When the adjusted $P_e(t)$ is less than 0 however deficit power has not been supplied, the consumers enter a P2p energy sharing mode. All the Type 2 and Type 3 consumers are motivated to buy or sell their battery energy at internal prices $z_{buy}(t)$ and $z_{sell}(t)$, respectively. Due to the limited battery energy, the consumers have to compete for the available energy in the batteries, either buy it at a lower price to save electricity cost or sell it at a higher price to make a profit. In essence, the prices presented in Figure 4.4 regulate consumers to supply their own load first before selling power to their peer, and

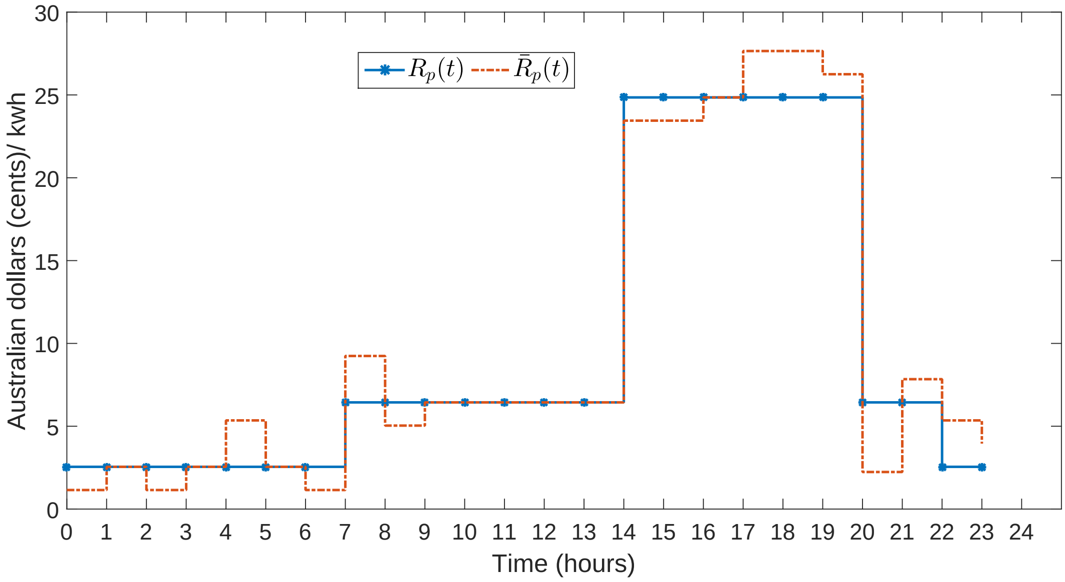


Figure 4.3. TOU electricity tariff and the battery charging tariff

to purchase electricity from their peers at a good price before purchasing emergency electricity. In essence, the prices presented in Figure 4.4 motivate consumers to self-supply first before purchasing electricity in the P2P energy sharing network, and motivate consumers to purchase electricity in the P2P energy sharing network before purchasing emergency electricity from the retailer.

4.3 GAME THEORETICAL RESULTS

The electricity consumers individually strategized between charging and remaining idle in the Battery charging mode and strategized between selling, buying and and remaining idle in the P2P energy sharing mode.

The three Type 1 consumers competed in a Nash equilibrium game for the surplus electricity when the discrepancy in Figure 4.5, Figure 4.6, and Figure 4.7 is greater than 0, and depending on the amount of surplus electricity, one of the three households, two of the three households or all three households are able to charge their BESS, as shown by the blue positive bar graph in Figure 4.5, Figure 4.6, and Figure 4.7. When a consumer charges their BESS with surplus electricity, the charging energy 0.56 kWh is reflected in the battery energy in Figure 4.5, Figure 4.6, and Figure 4.7. When the discrepancy in Figure 4.2 is less than 0, the three Type 1 consumers self-supply as shown by a decrease in the

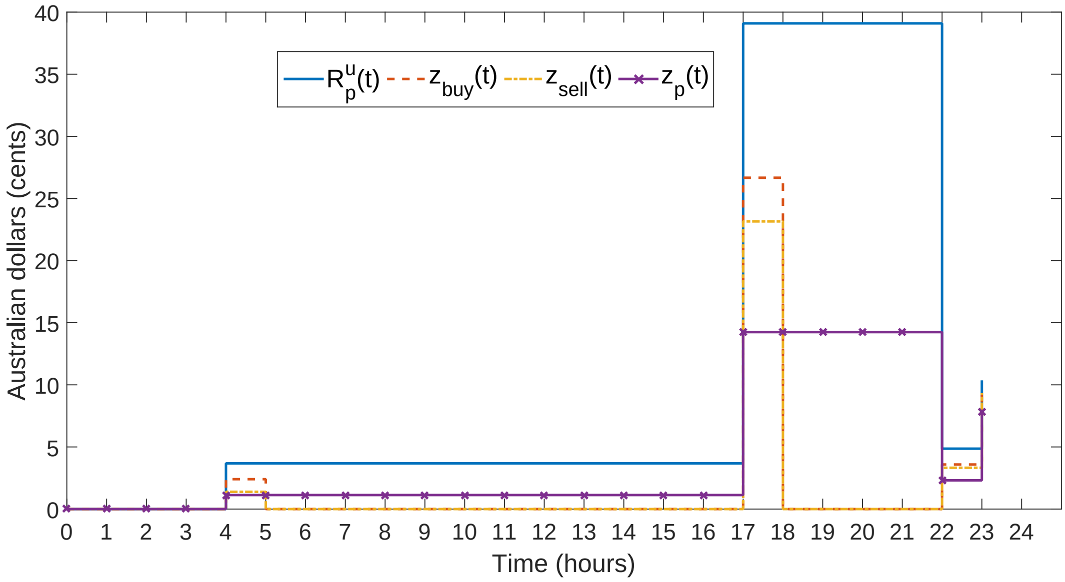


Figure 4.4. P2P energy sharing electricity prices

battery energy and a negative green bar graph, and purchase emergency electricity to meet their deficit supply, as shown by a positive black bar graph. It is worth noting that the legend is a representative of all possible actions that can occur at any given time, though they do not occur at that particular time.

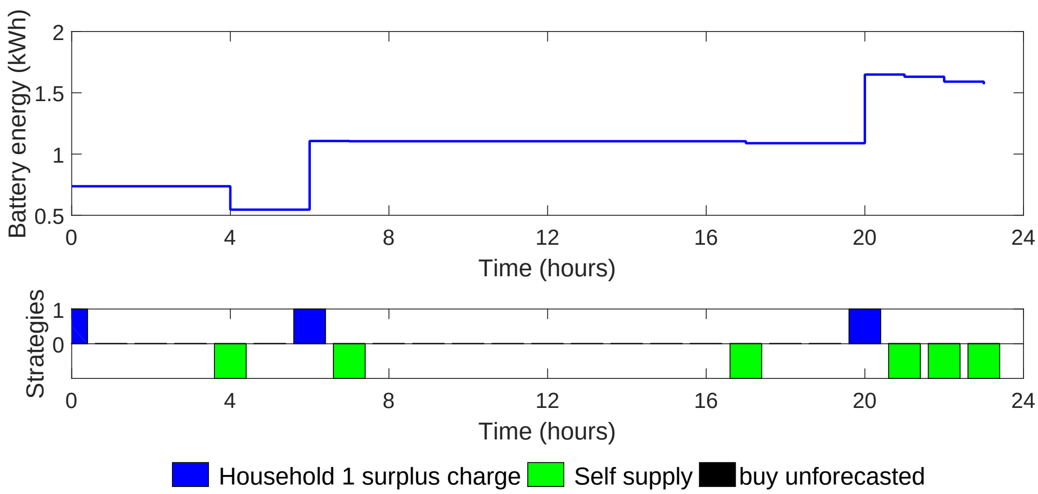


Figure 4.5. Type 1 consumer battery energy for load profile 1

The three Type 2 consumers competed in a Nash equilibrium game for the P2P energy when the

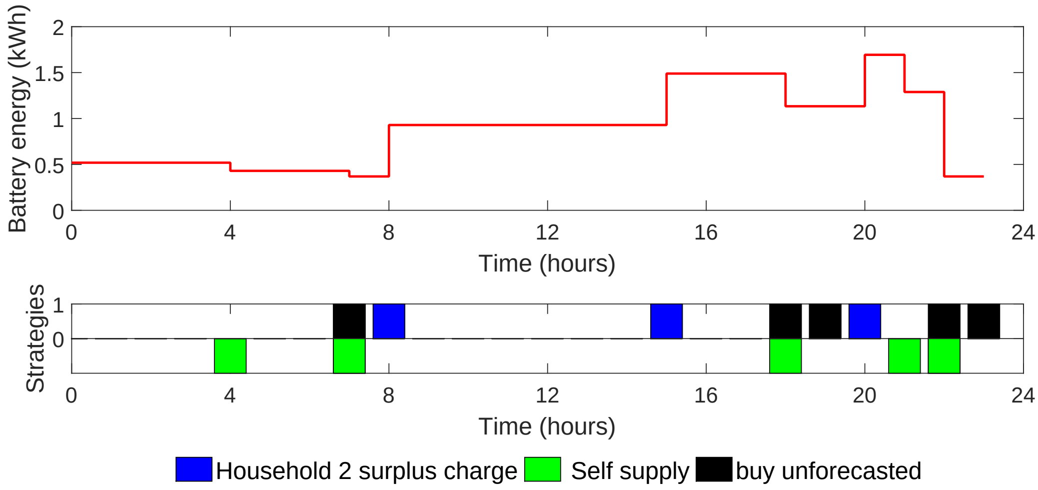


Figure 4.6. Type 1 consumer battery energy for load profile 2

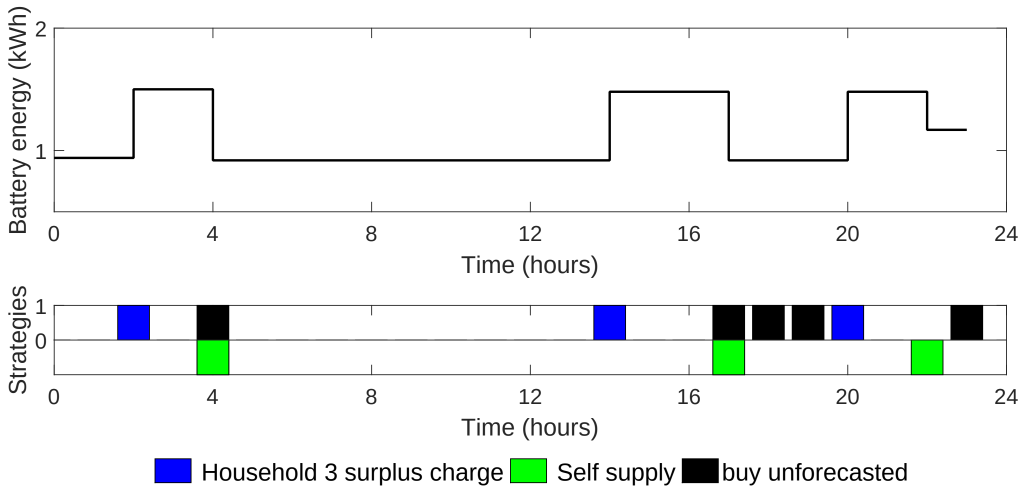


Figure 4.7. Type 1 consumer battery energy for load profile 3

discrepancy in Figure 4.2 is less than 0 to supply their deficit power, and depending on the amount of deficit power, one of the other two households or all two households are able to buy P2P energy. In the absence of P2P energy and presence of deficit supply, the three Type 2 consumers purchase emergency electricity to meet their deficit supply, as shown by a positive black bar graph in Figure 4.8.

The three Type 3 consumers competed in a Nash equilibrium game for the surplus electricity when the

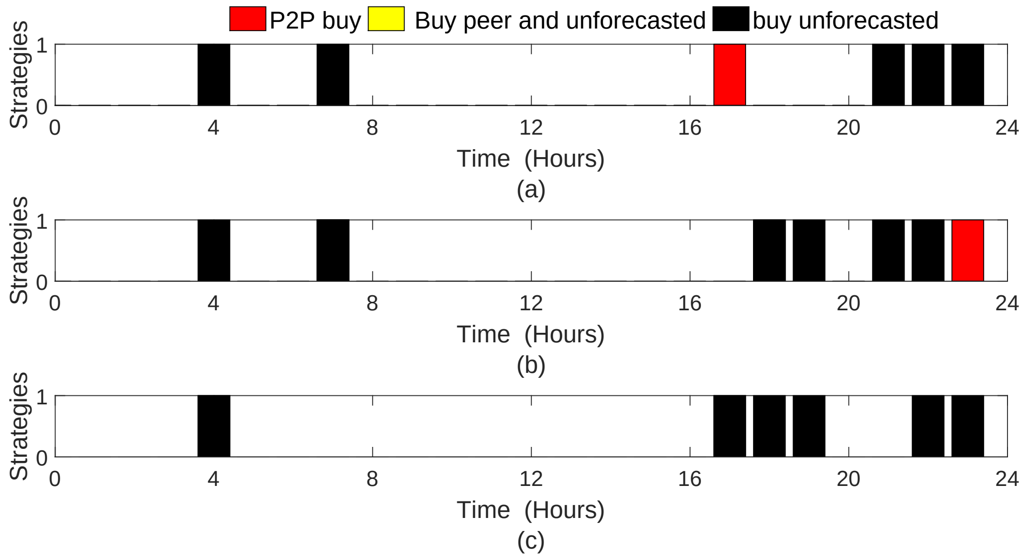


Figure 4.8. Type 2 consumer deficit supply actions for (a) load profile 1, (b) load profile 2 and (c) load profile 3

discrepancy in Figure 4.2 is greater than 0, and depending on the amount of surplus electricity, one of the three households, two of the three households or all three households are able to charge their BESS, as shown by the blue positive bar graph in Figure 4.9, Figure 4.10, and Figure 4.11. When a consumer charges their BESS with surplus electricity, the charging energy 0.56 kWh is reflected in the battery energy in Figure 4.9, Figure 4.10, and Figure 4.11. When the discrepancy in Figure 4.2 is less than 0, the three Type 3 consumers self-supply as shown by a decrease in the battery energy and a negative green bar graph in Figure 4.9, Figure 4.10, and Figure 4.11. When Type 3 consumers have deficit power after self supply, they compete in a Nash equilibrium game for the P2P energy as shown by a positive red bar graph, and depending on the amount of deficit power a household has, one of the other two households or all two households are compete in a Nash equilibrium game to sell their BESS energy as shown by a decrease in the battery energy and a negative red bar graph in Figure 4.9, Figure 4.10, and Figure 4.11. When a Type 3 consumer still has deficit power after P2P energy sharing, they purchase emergency electricity to meet their deficit supply, as shown by a positive black bar graph in Figure 4.9, Figure 4.10, and Figure 4.11. It is worth noting that a Type 3 consumer is able to simultaneously self-supply and buy electricity in the P2P energy sharing network, simultaneously self-supply and buy emergency electricity from the retailer, simultaneously self-supply and sell electricity in the P2P energy sharing network as shown buy a purple negative bar graph, and simultaneously buy P2P energy and buy emergency electricity from the retailer as shown by a positive yellow bar graph.

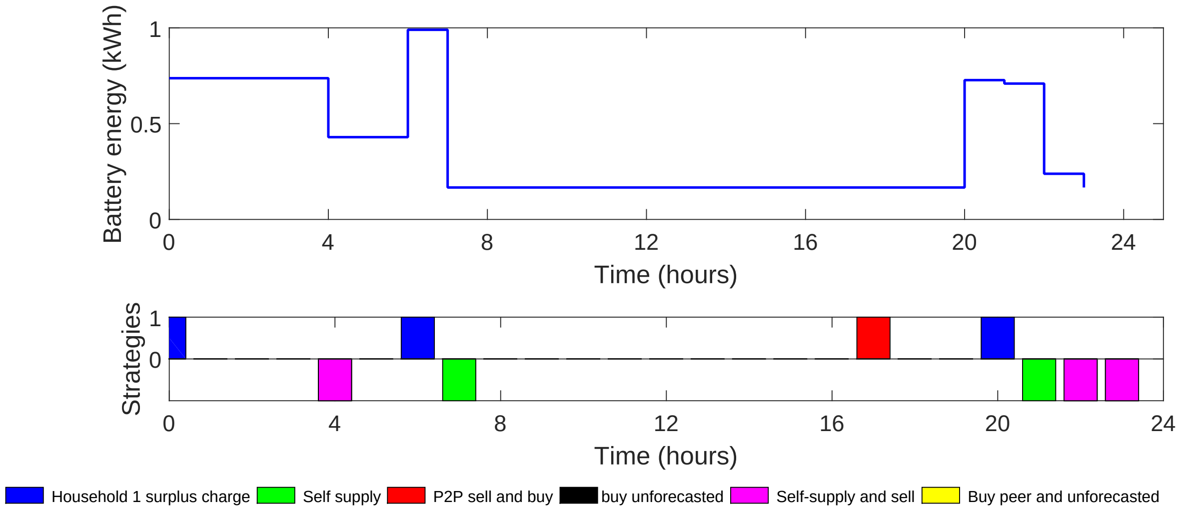


Figure 4.9. Type 3 consumer battery energy for load profile 1

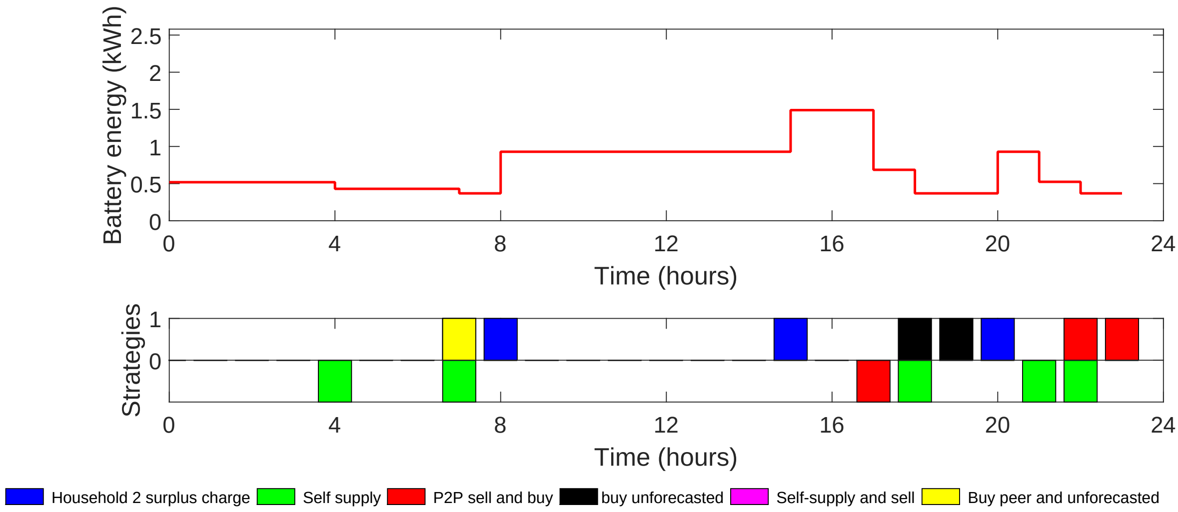


Figure 4.10. Type 3 consumer battery energy for load profile 2

4.3.1 Type 4 consumers

Figure 4.12 shows the time intervals Type 4 consumers purchased unforecasted electricity from the retailer to supply their deficit supply because Type 4 consumers neither employ batteries nor participate in P2P energy sharing.

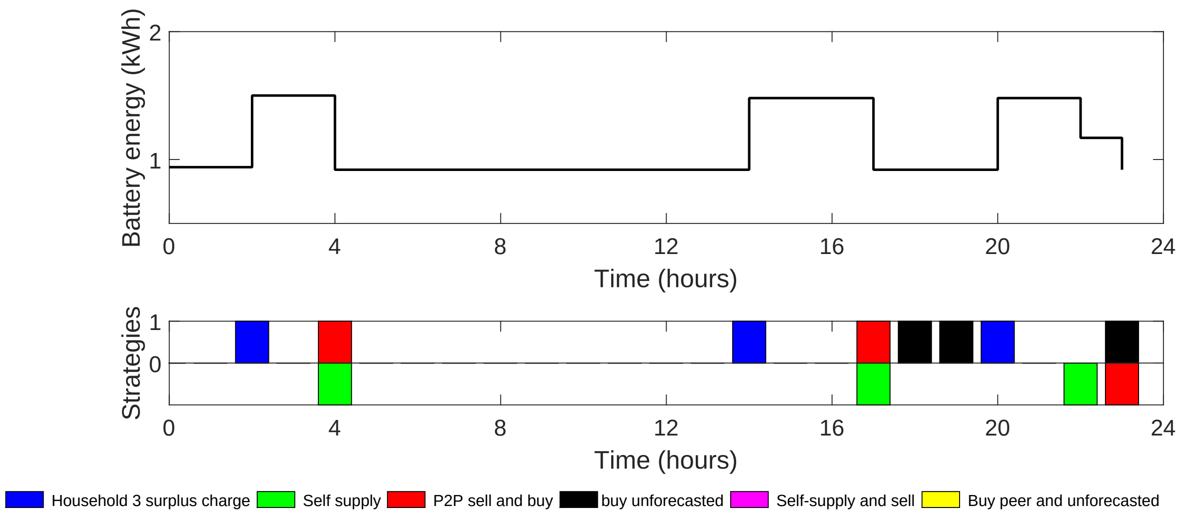


Figure 4.11. Type 3 consumer battery energy for load profile 3

Figure 4.13 shows the amount of electricity sold and Figure 4.14 shows the amount of electricity purchased by each consumer in the P2P energy sharing framework. It is evident that at certain time intervals, the consumer requesting to purchase electricity receives electricity from all the other consumers because the consumer chosen at Nash equilibrium to sell the electricity does not have enough battery electricity for the purchasing consumer. It is also evident that at some time intervals, a consumer receives requests to sell electricity from all the other consumers, that is one consumer requests first and the second consumer follows suit. In this case the two consumers compete to purchase electricity from the one consumer selling. The chosen consumer at Nash equilibrium purchases electricity first, and then the second consumer can purchase if the selling consumer still has electricity to sell.

4.4 ENERGY COSTS

The energy costs incurred by Type 1 consumers, Type 2 consumers, Type 3 consumers and Type 4 consumers with the load profile of household 1 are shown in Table 4.1. The energy costs incurred by Type 1 consumers, Type 2 consumers, Type 3 consumers and Type 4 consumers with the load profile of household 2 are shown in Table 4.2. The energy costs incurred by Type 1 consumer, Type 2 consumers, Type 3 consumers and Type 4 consumers with the load profile of household 3 are shown in Table 4.3.

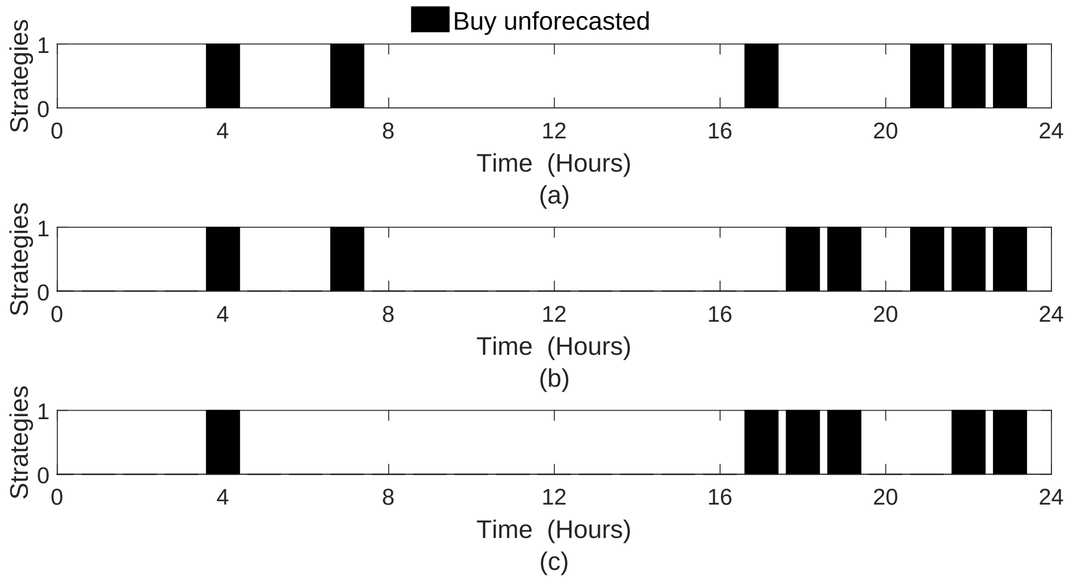


Figure 4.12. Type 4 consumer deficit load supply actions for (a) load profile 1, (b) load profile 2 and (c) load profile 3

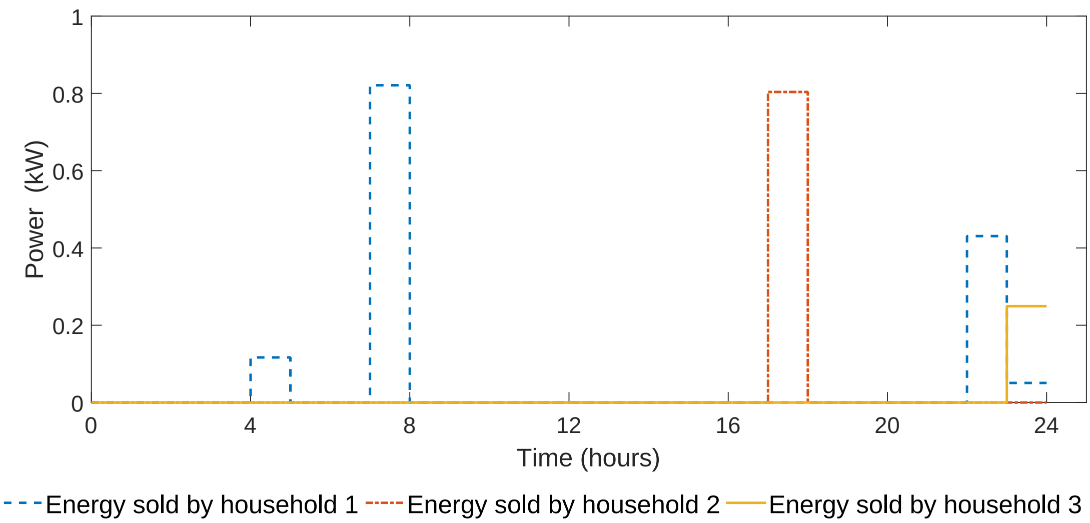


Figure 4.13. Amount of energy sold in the peer to peer energy structure

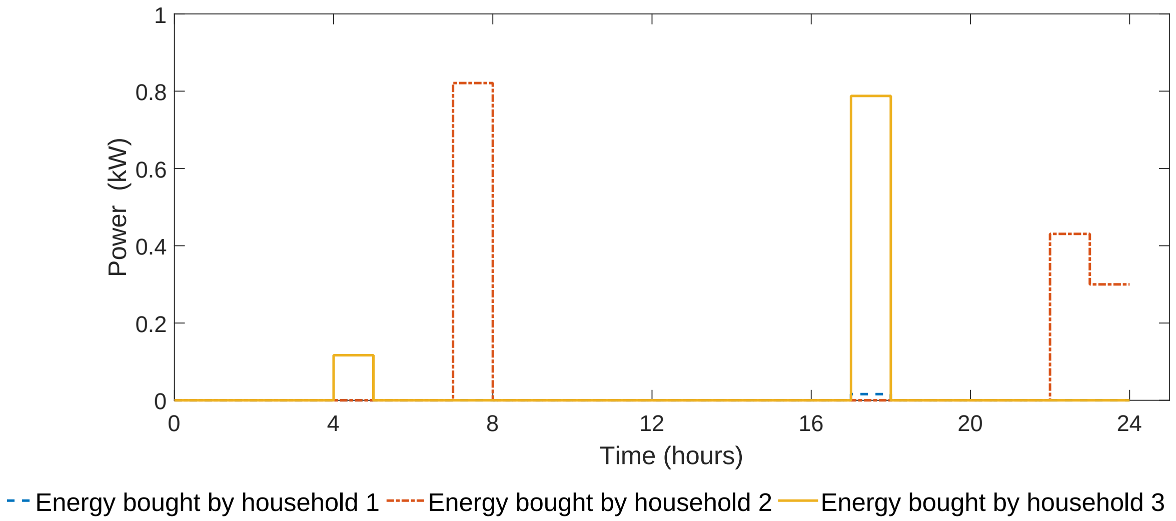


Figure 4.14. Amount of energy bought in the peer to peer energy structure

Table 4.1. A comparison of the energy costs incurred by the four types of consumers with household 1 load demand

Time (Hour)	Type 1 consumer (AUD)	Type 2 consumer (AUD)	Type 3 consumer (AUD)	Type 4 consumer (AUD)
1	1.07	1.07	1.07	1.07
2	1.15	1.15	1.15	1.15
3	1.15	1.15	1.15	1.15
4	1.18	1.18	1.18	1.18
5	0.90	1.39	0.75	1.39
6	0.75	0.75	0.75	0.75
7	0.62	0.62	0.62	0.62
8	1.60	1.61	1.05	1.61
9	1.73	1.73	1.73	1.73
10	1.64	1.64	1.64	1.64
11	1.59	1.59	1.59	1.59
12	1.81	1.81	1.81	1.81
13	1.74	1.74	1.74	1.74
14	1.65	1.65	1.65	1.65
15	7.23	7.23	7.23	7.23
16	9.79	9.79	9.79	9.79
17	12.77	12.77	12.7	12.77
18	12.89	13.34	5.48	13.34
19	13.76	16.55	-1.79	16.55
20	17.04	17.04	17.04	17.04
21	3.44	3.44	3.44	3.44
22	2.93	4.11	2.96	4.11
23	1.10	1.27	-0.71	1.27
24	1.15	1.38	1.90	1.38

Table 4.2. A comparison of the energy costs incurred by the four types of consumers with household 2 load demand

Time (Hour)	Type 1 consumer (AUD)	Type 2 consumer (AUD)	Type 3 consumer (AUD)	Type 4 consumer (AUD)
1	0,81	0,81	0,81	0,81
2	0,74	0,74	0,74	0,74
3	0,53	0,53	0,53	0,53
4	0,50	0,50	0,50	0,50
5	0,54	0,87	0,54	0,87
6	0,55	0,55	0,55	0,55
7	2,01	2,01	2,01	2,01
8	3,14	6,96	6,47	10,20
9	9,85	9,85	9,85	9,85
10	7,07	7,07	7,07	7,07
11	7,23	7,23	7,23	7,23
12	2,96	2,96	2,96	2,96
13	3,79	3,79	3,79	3,79
14	3,74	3,74	3,74	3,74
15	5,54	5,54	5,54	5,54
16	8,17	8,17	8,17	8,17
17	16,30	16,30	16,30	16,30
18	53,51	61,71	18,97	61,71
19	81,44	81,44	81,44	81,44
20	48,85	48,85	48,85	48,85
21	8,32	8,32	8,32	8,32
22	3,50	30,05	4,10	30,05
23	1,91	3,46	3,93	3,61
24	0,52	3,17	3,17	3,50

Table 4.3. A comparison of the energy costs incurred by the four types of consumers with household 3 load demand

Time (Hour)	Type 1 consumer (AUD)	Type 2 consumer (AUD)	Type 3 consumer (AUD)	Type 4 consumer (AUD)
1	0,46	0,46	0,46	0,46
2	0,52	0,52	0,52	0,52
3	0,46	0,46	0,46	0,46
4	0,52	0,52	0,52	0,52
5	1,08	2,76	1,27	3,00
6	0,49	0,49	0,49	0,49
7	1,35	1,35	1,35	1,35
8	2,52	4,22	1,57	4,22
9	3,36	3,36	3,36	3,36
10	1,13	1,13	1,13	1,13
11	0,50	0,50	0,50	0,50
12	3,31	3,31	3,31	3,31
13	0,50	0,50	0,50	0,50
14	0,63	0,63	0,63	0,63
15	2,18	2,18	2,18	2,18
16	2,06	2,06	2,06	2,06
17	30,04	30,04	30,04	30,04
18	2,50	19,44	19,44	21,67
19	115,50	135,19	135,19	136,52
20	62,08	62,08	62,08	62,08
21	2,35	2,35	2,35	2,35
22	1,725	5,63	1,85	5,63
23	1,81	2,13	1,25	2,13
24	0,51	0,76	-1,77	0,76

CHAPTER 5 DISCUSSIONS

5.1 CHAPTER OVERVIEW

This chapter presents a discussion of the results presented in Chapter 4 and determines the effectiveness of the objective function in 3.

5.2 ELECTRICITY COST

This section gives an analysis of the first research question presented in section 1.3.

As the four categories of consumers were under the same conditions that influence energy cost, that is the same surplus electricity price, same P2P energy sharing price, surplus electricity, deficit electricity and the same outcome of the Nash equilibrium game, the retailer was able to make a fair comparison of the energy costs. Figure 5.1 shows a comparison of the energy costs for consumers with load profile 1. Figure 5.2 shows a comparison of the energy costs for consumers with load profile 2. Figure 5.3 shows a comparison of energy costs for consumers with load profile 3. It can be seen that Type 3 consumers can have a negative energy cost at the time periods when they sold electricity to their peers, and as a result, their energy bill is reduced to a negative, and in such a case, the retailer owes the consumer. Type 1 consumers may incur energy costs less than Type 3 consumers when they both self-supply because it will have more energy in the battery as it does not sell it.

Table 5.1 shows the tabulated sum of energy cost for the four different types of consumers. Type 4 consumers incurred the highest costs because they did not have batteries nor participated in P2P energy sharing. Type 2 consumers incurred the high costs because they did not have batteries to

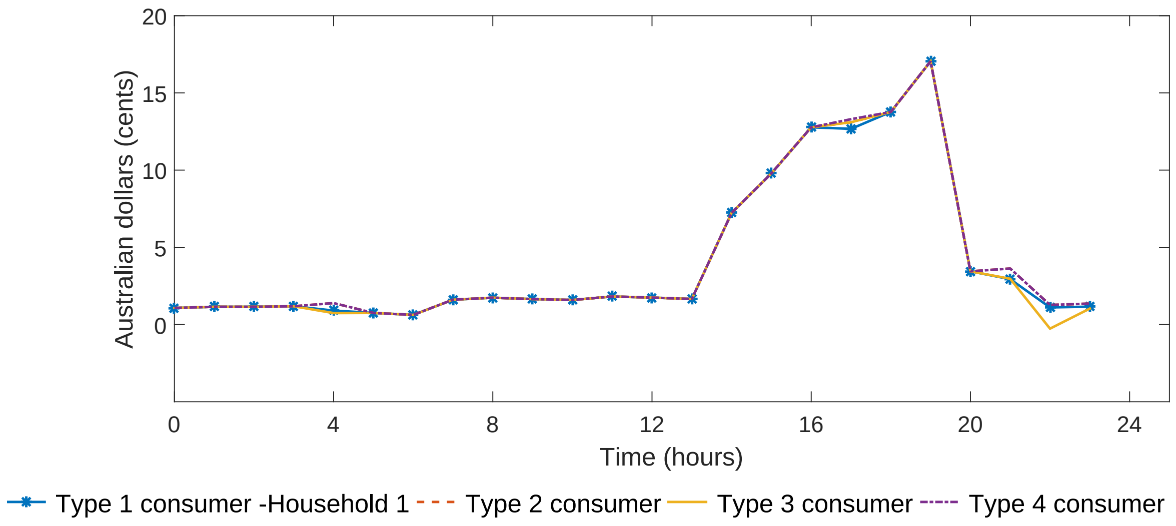


Figure 5.1. A comparison of energy costs for consumers with load profile 1

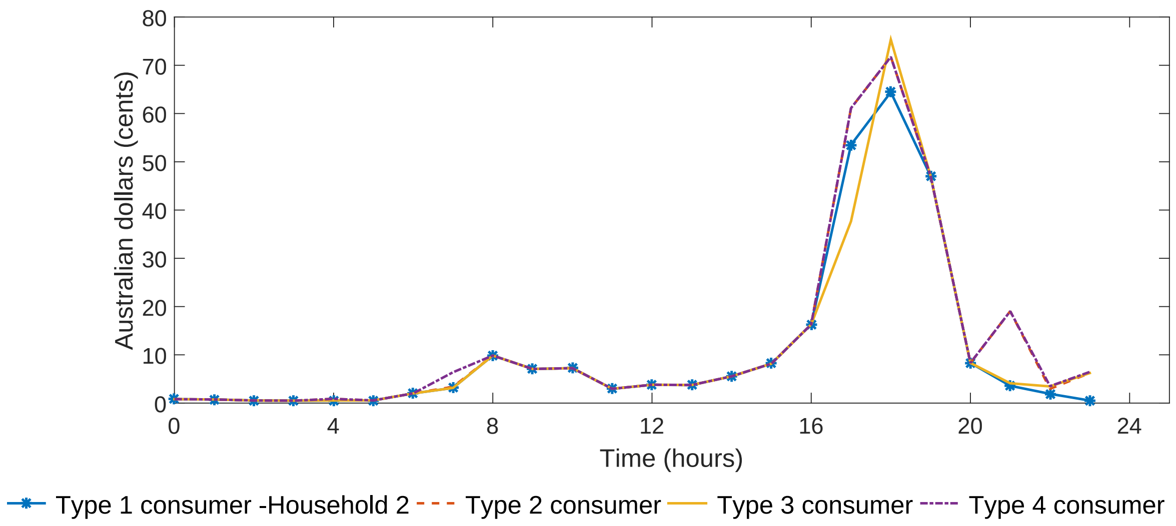


Figure 5.2. A comparison of energy costs for consumers with load profile 2

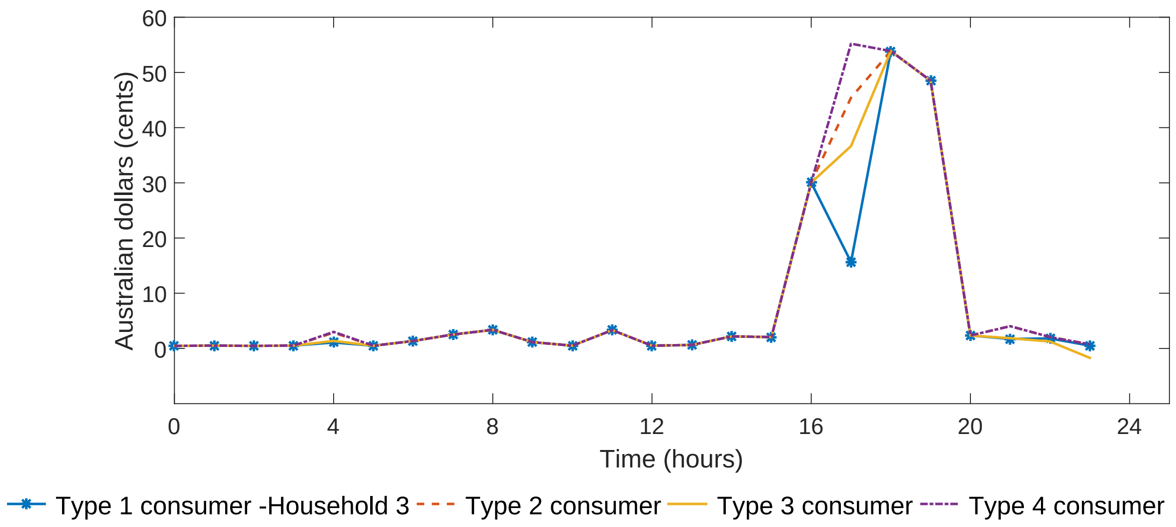


Figure 5.3. A comparison of energy costs for consumers with load profile 3

Table 5.1. A comparison of energy costs for the three models

	Load profile 1 (AUD)	Load profile 2 (AUD)	Load profile 3 (AUD)
Type 1	1.01	2.53	1.93
Type 2	1.04	2.97	2 11
Type 3	1.00	2.42	1 86
Type 4	1.04	3.01	2.21

self-discharge, which is the cheapest option. Instead they bought electricity from their peers and unforecasted electricity to satisfy their deficient loads. Type 1 consumers also incurred high energy costs, because though they self-discharge, they did not participate in energy sharing and hence had tp buy unforecasted electricity from the retailer which costs more than the P2P energy buying cost. The Type 3 consumers incurred the least energy cost they self-discharge and participate in P2P energy sharing first before buying unforecasted electricity to satisfy their deficient loads. Comparing to the Type 4 consumers, all other types of consumers obtained some electricity cost savings. The relative savings percentage are presented in Table 5.2.

Type 3 consumers obtained the highest percentage of profits because of their participation in the two

Table 5.2. Percentage of cost savings with respect to the Type 4 consumers

	Load profile 1 (%)	Load profile 2 (%)	Load profile 3 (%)
Type 1	2.2	15.7	12.7
Type 2	1.8	1.3	4.5
Type 3	3.5	19.6	15.6

modes, battery charging and P2P energy sharing. As the retailer is interested in finding out which type of consumer yields the most profit for him, Table 5.3 summarises how much the retailer profits from each type of consumer. Though both Type 1 consumers and Type 3 consumers use up all the excess power to charge their batteries, that would otherwise be wasted, Type 3 consumers still result in higher profits for the retailer because they mitigate more of their deficit power by participating in P2P energy sharing, hence requiring less unforecasted electricity, which increases the expenditure of the retailer. Type 2 consumers participate in P2P energy sharing however, because they do not have batteries to self-supply, they require additional emergency electricity, which reduces the profit for the retailer. Type 4 consumers require the most emergency electricity because they do not self-supply and participate in P2P energy sharing, hence they yield the least profits for the retailer.

Table 5.3. The retailer profit from different consumers

Type of consumer	Profit (AUD)
Type 1	3.82
Type 2	3.75
Type 3	4.10
Type 4	3.28
Total profit	1494.3

5.3 ELECTRICITY RETAIL

This section gives an analysis of the second research question presented in section 1.3.

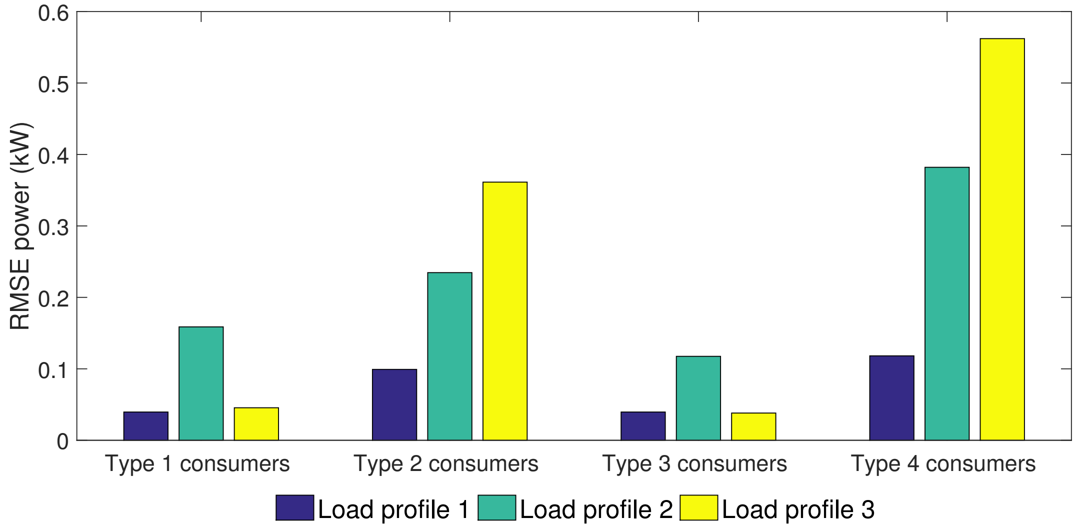


Figure 5.4. Root-mean squared error for different types of consumers

5.3.1 Supply and demand discrepancy root-mean squared error

When considering the discrepancy between supply and demand before and after the battery charing and P2P energy sharing games, the root-mean square errors (RMSE) of the supply demand discrepancy are calculated and illustrated in Figure5.4. Type 3 consumers provide the lowest RMSEs, due to the dual benefits of battery charging and P2P energy sharing. The Type 4 consumers provide the highest RMSE because they do not absorb excess during high-supply low-demand periods, and have to purchase emergency electricity during low-supply high-demand periods.

CHAPTER 6 CONCLUSION

This dissertation presented an electricity regulation system for a day-ahead electricity retail market. The objective of the system minimizes the electricity cost of the electricity consumers and maximises the profits of the electricity retailer, by minimizing the excess electricity and deficit electricity in the electricity retail market. The electricity retail market comprised of electricity consumers with batteries and consumers without batteries. Electricity consumers with batteries took advantage of the low prices excess electricity to charge their batteries during high-supply low-demand periods in the electricity retail market. The electricity consumers with batteries were able to supply their deficit demand with their battery energy during low-supply high-demand periods, whereas electricity consumers without batteries buy the highly priced unforecasted electricity. The electricity retail market allowed some consumers with batteries and without batteries to participate in purchasing electricity from their neighbours in a P2P energy sharing network. The electricity in the P2P energy sharing network is priced low, and electricity consumers were all eager to purchase the low electricity from their neighbours with the aim of minimizing their electricity cost.

The analysis of the results presented in this dissertation showed that electricity consumers with batteries and participated in the P2P energy sharing network achieved the lowest electricity cost and provided the electricity retailer with the highest profits, as compared to electricity consumers that incorporated batteries but did not participate in P2P energy sharing, electricity consumers that did not incorporate batteries but participated in the P2P energy sharing network and consumers that neither incorporated batteries nor participated in the P2P energy sharing network.

6.1 RECOMMENDATIONS AND FUTURE RESEARCH

1. In the current work, the proposed load forecasting tool is a simple DA ANN model. Future research can implement a more sophisticated load forecasting model with deep data and machine learning for more accurate predictions. The high level model could further improve the electricity supply and demand balancing model.

2. This study focused on balancing electricity supply and demand for a 24 hour period. Future research can extend the optimisation horizon to a month or a year to take into account factors that affect load demand over longer period, such as land-use and economical variations. Energy cost savings over longer time horizons could provide more convincing for electricity consumers and retailer to implement the proposed system.

3. In the current work, there existed multiple Nash equilibria at a time, and the choice of either Nash equilibrium gave the optimal frequency control solution. This study performed a randomization between the Nash equilibria considering only the battery energy of the consumers and not the forecasted demand in the coming time slots. An example, if a consumer is likely to need additional electricity in the next time slots, they should opt not to sell electricity in the P2P energy sharing network, to avoid buying electricity in the P2P energy sharing network or worse unforecasted electricity from the retailer, as battery energy is more affordable. A more sophisticated selection of the Nash equilibrium can improve the energy costs of consumers.

4. In the current study, the game is a non-cooperative game as consumers are generally selfish individuals who only care about maximizing their own benefits. Future work can consider a cooperative game, because though a challenge for individuals to work together, cooperation games can bring more energy savings for all the consumers.

5. In this study, the electricity regulation model supplied unforecasted electricity to consumers with deficit supply that have not been supplied, which increased their energy costs. It will be interesting to extend this work by giving consumers freedom to choose whether to use unforecasted electricity or remain unsupplied and introduce a willingness and discomfort variable. Similarly, demand side management can be extended to this work to shift shiftable loads to time periods with affordable electricity supply.

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