Game-theoretic methods for small-scale demand-side management in smart grid

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Game-theoretic Methods for Small-scale Demand-side Management in Smart Grid

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A thesis in fulfillment of the requirements for the degree of
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Increasing electricity demand with inadequate power generating resources has become a key challenge for power system operators. Adding extra power generating sources to meet peak electricity demand can reduce the sustainability of the electricity grid and increase energy generation cost to power system operators. Demand-side management is essential to smart grid because it manages peak electricity demand without requiring major upgrades to existing grid infrastructure. Successful demand-side management strategies include employing distributed energy resources, such as renewable energy generation, near end-users to satisfy users' peak energy demand.

The primary goal of this dissertation is to devise and study novel decentralised energy trading systems for small-scale demand-side management incorporating a community energy storage (CES) device and customer-owned photovoltaic (PV) energy generation. First, we introduce an energy trading system between a CES device and residential PV energy users in a neighbourhood area network. In the energy trading system, users decisions to minimise their individual energy costs are studied by implementing a non-cooperative dynamic game. Then, we develop a hierarchical energy trading system between the CES device and the users, implementing a non-cooperative Stackelberg game, to enable both the CES operator and the residents to maximise their individual payoffs. Our results demonstrate that the proposed systems offer significant electricity cost savings for users, increased CES operator revenue, and peak-to-average load ratio reductions. Moreover, the systems are shown to be robust to imperfect information with significant forecast errors in demand and PV energy.

Next, the impacts of non-ideal participating actions of users, that are not completely rational, on the hierarchical energy trading are investigated using a prospect-theoretic approach. The results demonstrate that the benefits of the energy trading system are robust to users' actions when they significantly deviate from complete rationality. Finally, we use prospect theory to investigate the impact of non-ideal participating actions of multiple electric vehicle (EV) aggregators on a non-cooperative game-theoretic EV charging system. Extensive numerical analysis shows that the performance of the EV charging system, in terms of energy cost reductions and peak-to-average ratio reductions, is resilient to aggregators' non-ideal participating actions.

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Abstract

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The primary goal of this dissertation is to devise and study novel decentralised energy trading systems for small-scale demand-side management incorporating a community energy storage (CES) device and customer-owned photovoltaic (PV) energy generation. First, we introduce an energy trading system between a CES device and residential PV energy users in a neighbourhood area network. In the energy trading system, users' decisions to minimise their individual energy costs are studied by implementing a non-cooperative dynamic game. Then, we develop a hierarchical energy trading system between the CES device and the users, implementing a non-cooperative Stackelberg game, to enable both the CES operator and the residents to maximise their individual payoffs. Our results demonstrate that the proposed systems offer significant electricity cost savings for users, increased CES operator revenue, and peak-to-average load ratio reductions. Moreover, the systems are shown to be robust to imperfect information with significant forecast errors in demand and PV energy.

Next, the impacts of non-ideal participating actions of users, that are not completely rational, on a hierarchical energy trading system between the CES device and users are investigated using a prospect-theoretic approach. The results demonstrate that the benefits of the energy trading system are robust to users' actions when they significantly deviate from complete rationality. Finally, we use prospect theory to investigate the impacts of non-ideal participating actions of multiple electric vehicle (EV) aggregators on a non-cooperative game-theoretic coordinated EV charging system. Extensive numerical analysis shows that the performance of the EV charging system, in terms of energy cost reductions and peak-to-average ratio reductions, is resilient to aggregators' non-ideal participating actions.

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List of Abbreviations

BNS:	Baseline Net-metering System
CES:	Community Energy Storage
EUT:	Expected Utility Theory
EV:	Electric Vehicle
FC:	Fully Cooperative
PS:	Proposed System
PT:	Prospect Theory
PV:	Photovoltaic
SOC:	State-Of-Charge

List of Variables and Notations

$\mathcal{V}$:	Set of players in a generic non-cooperative game
Q:	Set of all users in the neighbourhood area network
$\mathcal{P}$:	Set of participating users
$\mathcal{N}$:	Set of non-participating users
$\mathcal{M}$:	Set of EV aggregators
$\mathcal{B}_i$:	Set of EVs controlled by aggregator i
$\mathcal{S}(t)$:	Set of surplus users with excess PV energy at time t
$\mathcal{D}(t)$:	Set of deficit users with energy deficits at time t
$g_n(t)$:	PV energy generation of user n at time t
$e_n(t)$:	Energy demand of user n at time t
$x_n(t)$:	Energy traded with the CES device by user n at time t
$l_Q(t)$:	Energy traded between the CES device an the grid at time t
$l_n(t)$:	Energy traded with the grid by user n at time t
$s_n(t)$:	Surplus PV energy of user n at time t
$q(t)$:	Charge level of the CES device at the end of time t
$a(t)$:	Unit energy price of the CES device time t
$p(t)$:	Unit energy price of the grid at time t
$L(t)$:	Total grid load at time t
$L_{\mathcal{N}}(t)$:	Total grid load of the users $\mathcal{N}$ at time t
$L_{-n}(t)$:	Total grid load of the community except user n at time t

$C_n(t)$:	Energy cost of user n at time t
$P_n(t)$:	Payment received by user n from the CES operator at time t
$F_n(t)$:	Cost paid to the grid by user n at time t
$\boldsymbol{X_n(t)}$:	Strategy set of user n at time t
$L_{b,t}$:	Base grid load at time t
$r_{n,t}$:	Charging rate of EV n at time t
e_n:	Energy demand of EV $n \in \mathcal{B}_i$
$g_{i,t}$:	Weighting parameter of EV aggregator t at time t
$X_{\mathcal{P}}(t)$:	Aggregate CES energy trading amounts of the users $\mathcal{P}$
$C_{CES}(t)$:	Cost of the CES operator at time t
$S_{\mathcal{P}}(t)$:	Aggregate surplus energy of the users $\mathcal{P}$ at time t
$S_{n,\text{init}}$:	Initial SOC level of EV n
$S_{n,\max}$:	Maximum SOC level of EV n
E_i:	Total energy demand of EV aggregator i
η_i:	EV charger efficiency of EV aggregator i
R_n:	Maximum charging rate of EV n
R:	Revenue of the CES operator
$\mathcal{Q}$:	Strategy set of the CES operator
Υ:	Stackelberg game between the CES operator and the users $\mathcal{P}$
$\mathcal{L}$:	CES operator
$\boldsymbol{a}$:	Vector of CES energy price; $\boldsymbol{a} \in \Re^{M\times 1}$
$\boldsymbol{l_Q}$:	Vector of grid energy of the CES device; $\boldsymbol{l_Q} \in \Re^{H\times 1}$
$\boldsymbol{\rho}$:	Matrix of decision variables of the CES operator
$\mathcal{G}$, Γ, G:	Non-cooperative games among the users $\mathcal{P}$ at time t
Ω:	Two-stage non-cooperative game among EV aggregators

Ψ:	Set of proper subgames at the second stage of the game Ω
G_σ:	Subgame among aggregators with respect to EV charging start time strategy profile σ
Φ:	Non-cooperative game among the aggregators $\mathcal{M}$ at the first stage of the game Ω
$\mathcal{X}$:	Strategy set of the users $\mathcal{P}$ at time t
$\mathcal{C}$:	Set of cost functions of the users $\mathcal{P}$ at time t
$\mathcal{I}_i$:	Set of all possible EV charging start times of aggregator i
Ξ:	Participation time selection game of the users $\mathcal{P}$
$\boldsymbol{K_n}$:	Strategy set of user n in the game Ξ
U_n:	Cost of user n in the game Ξ
h_n:	Energy trading start time of user n
$y_n(h_n)$:	Probability of selecting h_n by user n
λ_i:	Minimum number of time slots that EV aggregator i requires to charge all EVs in $\mathcal{B}_i$
$E_n^{EUT}(.)$:	Expected cost of user n under expected utility theory
$E_n^{PT}(.)$:	Expected cost of user n under prospect theory
$Q_{i,\Phi}^{\mathrm{EUT}}$:	Expected payoff of aggregator i of the game Φ under expected utility theory
$Q_{i,\Phi}^{\mathrm{PT}}$:	Expected payoff of aggregator i of the game Φ under prospect theory
R^{EXP}:	Expected revenue of the CES operator
$\mathcal{A}_i$:	Set of actions available to player $i \in \mathcal{V}$
J_i:	Utility function of player $i \in \mathcal{V}$
$p(\mathcal{A}_i)$:	Set of probability distributions over the action set $\mathcal{A}_i$
b_i:	Strategy of user $i \in \mathcal{V}$
κ:	Parameter that quantifies the distortion between subjective and objective evaluations

$w(.)$:	Weighting function
$\mathcal{T}$:	Time period of analysis
M:	Total number of time steps in $\mathcal{T}$
I:	Number of participating users
α:	Leakage rate of the CES device
β^+, β^-:	Charging and discharging efficiencies of the CES device; $(0 < \beta^+ \leq 1,\ \beta^- \geq 1)$
δ_t, ϕ_t:	Time-of-use tariff constants of the grid at time t
Q_M:	Maximum energy capacity of the CES device
$L_{\max}$:	Maximum allowable grid load
v, w:	Indices of rows and columns of a matrix
θ:	Real-valued scalar
r:	Iteration number
τ:	Small positive value
ω:	Random value from the uniform distribution $[-1, 1]$
σ:	Constant; $0 \geq \sigma \geq 1$

Chapter 1

Introduction

1.1 Motivation and Background

1.1.1 Smart Grid

The global rise in electricity demand has necessitated major upgrades to the existing electricity grid infrastructure through adding extra power generating sources such as fast responding generators. Adding extra power generating units to meet growing energy demand would not perpetuate the sustainability of the electricity grid as it can underutilise the power generating capacity of the grid. The next-generation electricity grid, smart grid, synthesises advanced communication and control technologies with the existing power grid infrastructure to enhance the reliability and the quality of power while maintaining the sustainability of power generation. Smart grid is an electricity network that consists of intelligent power nodes that can manoeuvre energy consumption, production, and distribution efficiently. The use advanced control technologies in smart grid provides more capacity to transmit electricity at lower rates to end-users than in the conventional grid [Saad et al., 2012]. One of the key attributes of smart grid is that it instigates interactions among smart appliances, micro generation, smart meters, and customer loads to facilitate demand-side energy management through making electricity subscribers aware of their real time energy usage and electricity prices. Moreover, it opens access to electricity markets through increasing transmission paths and accumulating different ancillary services along with demand-supply initiatives [Ekanayake et al., 2012]. The diversity of operation of smart grid is illustrated in Fig. 1.1 [Zhu et al., 2012b].

1.1.2 The Importance of Demand-Side Management

Demand-side management is regarded as one of the essential elements in smart grid to regulate peak electricity demand efficiently with inadequate power generating capabilities

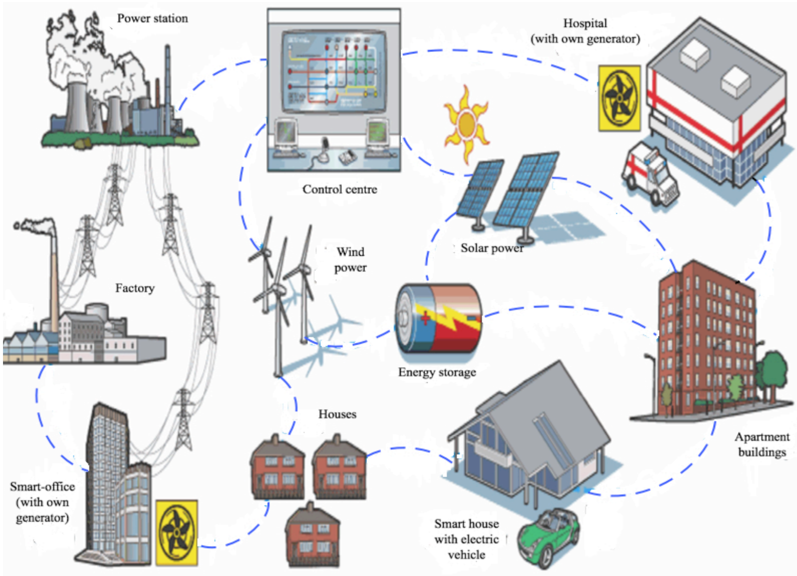

Fig. 1.1: An illustration of smart grid [Zhu et al., 2012b].

[Ekanayake et al., 2012]. Demand-side management encompasses the programs deployed by electric utility companies to manage energy consumption profiles of end-users of the power grid. These programs constitute of energy conservation strategies, fuel substitution methods, and load management methods that reduce or time-shift energy consumption of residential, commercial or industrial energy customers [Mohsenian-Rad et al., 2010]. Generally speaking, utility companies, with the knowledge of users' time-of-use energy consumption preferences, encourage users to participate in demand-side management by offering monetary incentives such as billing discounts.

Through managing peak grid energy demand, demand-side management renders various benefits to power system operators, customers as well as to the environment. Some of the important benefits can be identified as follows.

- Demand-side management allows the utilisation of available power generating capacity so that installation of new power generation and transmission infrastructure is not indispensable to support escalating energy demand.

- It also helps to mitigate grid instabilities, that occur as a consequence of peak energy demand, by shifting peak demand to non-peak hours where loads can be served without stressing the power grid.

- Effective demand-side management encourages the utilisation of renewable energy generation, ranging from large-scale renewable power generation to behind-the-meter renewable power generation, to reduce large carbon footprints caused by fossil-fuel power plants.

- Demand-side management can induce customer response by exploiting consumer-owned onsite generation such as rooftop photovoltaic (PV) power and can enable users to make monetary benefits such as energy cost reductions through energy trading.

1.1.3 Distributed Energy Generation

The conventional power grid is primarily designed for centralised energy generation and transmission where bulky electricity generating plants transmit power to end-users across large geographical distances. This, consequently, degrades the quality of power due to losses pertinent to long-distance transmission of energy [Kumar et al., 2015]. The rapid growth of distributed energy resources such as small-scale renewable energy generation and energy storage devices close to end-users has provided a promising means to convert the centralised grid infrastructure into a more distributed paradigm where power can be generated and distributed close to end-users with minimal power losses. Integrating distributed energy resources with demand-side management can deliver economic and environmental benefits to power system operators as well as to energy consumers through maintaining efficiency and diversity of electricity supply.

Popular technologies of distributed energy generation include wind power, distributed energy generation with bio-fuels, microgeneration, and PV power (solar power) [IET, 2006]. In particular, the global market for PV power generation at residential premises has been exponentially increasing due to cheaper and environment-friendly power generation [Marlene and Suzanna, 2015]. Additionally, energy storage devices play vital role in distributed energy generation with their ability to mitigate challenges associated with renewable power resources such as solar and wind [Heussen et al., 2012]. The application of energy storage devices at customer premises has been gaining momentum with the popularity of electric vehicles (EVs) and household-distributed renewable energy generation capabilities [Andrew, 2015].

1.1.4 Distributed Energy Storage for Residential Energy Applications

Distributed energy storage devices for residential community energy applications are known as community energy storage (CES) devices [Zhu et al., 2012b]. A CES device is an edge-of-grid energy storage application, which is located close to residential energy consumers, and exploits high power density battery technologies such as lithium ion to serve multiple residential consumers who live far way from large electricity generating plants [Arghandeh et al., 2014]. CES devices can be used to facilitate demand-side management of residential neighbourhood area networks, that consist of multiple residential buildings [Ekanayake et al., 2012], by utilising their energy storage capability to accumulate energy from the grid or from renewable energy resources, which can then be dispatched to support peak energy demand of users. In particular, CES devices can be effectively used to utilise renewable energy generation closer to energy users with minimal power losses [Arghandeh et al., 2014]. Innovative demand-side management methods with CES devices can encourage residential energy users who possibly own distributed energy generation to trade energy with the storage devices and thereby stimulate consumer participation towards achieving successful load management. With the rapid growth of solar mini power grids such as Melbourne's Codstream Network [Bleby, 2016], novel strategies for small-scale demand-side management with CES devices would play a vital role in the future energy grid. Fig. 1.2 depicts the basic configuration of a CES device within a neighbourhood area network [Zhu et al., 2012b].

1.2 Objectives and Contributions

In consumer-centric demand-side management that intends to employ active consumer participation by utilising consumer-owned energy resources, two straightforward questions would naturally arise; "*how would users benefit through participating in such programs*?", and "*what if all participants do not behave according to the expected plans in these programs*?". This thesis aims to answer these two important questions within the context of user-centric demand-side management that intends to procure contribution of users.

The primary objective of this thesis is to investigate novel decentralised energy trading systems for small-scale demand-side management, e.g., at the scale of a residential gated community, using a CES device and household-distributed PV power generation.

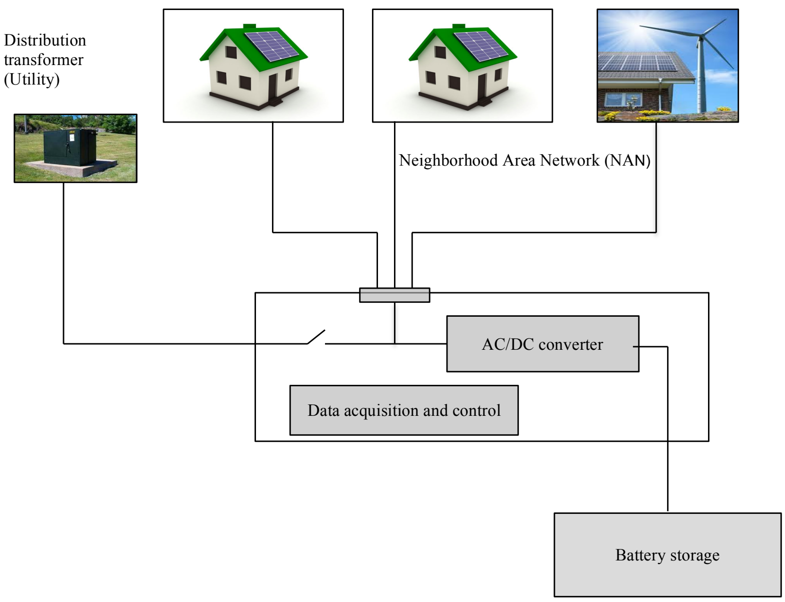

Fig. 1.2: Basic configuration of a CES system [Zhu et al., 2012b].

Subsequent to the main goal, the research focuses on the following key attributes.

i). Apprehend independent energy trading actions among participating entities

ii). Study the ability to optimise individual objectives of participating entities in decentralised way

iii). Investigate realistic consumer behavioural impacts on demand-side management

In order to study independent interactions of participants in the energy trading systems, we develop mathematical frameworks based on non-cooperative game theory. Then, we extend the game-theoretic frameworks to study potential non-ideal user behaviour in demand-side management by incorporating users' non-ideal actions, that are not completely rational, with the use of prospect theory. The main contributions of the research can be summarised as follows.

1. In Chapter 3, the novel energy trading system proposed in [Mediwaththe et al., 2016b] is presented. The energy trading system is implemented between a CES device and residential energy users with rooftop PV panels to regulate peak energy demand on the grid without reshaping users' regular energy demand patterns. We develop a non-cooperative dynamic game among the users and prove that the game obtains Pareto-efficient unique Nash equilibrium strategies for optimal CES dispatching. At the equilibrium, the peak grid energy load is significantly regulated while the participating users receive cost savings. We further show that the system is benefited by an increasing fraction of participating users.

2. In Chapter 4, we present the fully-competitive hierarchical energy trading system between a CES device and PV energy users proposed in [Mediwaththe et al., 2016a]. By developing a non-cooperative Stackelberg game, we studied autonomies of both the CES operator and the users to maximise personal utilities. We prove that the non-cooperative Stackelberg game with the fully-competitive CES operator has a unique Stackelberg equilibrium where the users obtain unique Pareto-optimal Nash equilibrium CES energy trading strategies.

3. Additionally, the fully-competitive Stackelberg game-theoretic energy trading system in Chapter 4 is compared with two other potential energy trading systems with different CES operator structures: a centralised cooperative CES operator and a benevolent CES operator. Through an extensive numerical performance analysis, we show that

- Unlike in the centralised cooperative system, both the CES operator and the participating users are simultaneously benefited in the proposed fully-competitive system while the grid achieves load levelling.
- The community economic benefit is greater with the fully-competitive system than the system with the benevolent CES operator, and the fully-competitive system can be implemented effectively with the least CES battery storage capacity of the three models.

4. In Chapter 5, through a numerical performance analysis, we show that the benefits of the proposed energy trading systems in Chapter 3 and Chapter 4 are significantly robust to imperfect information with respect to forecast errors of PV energy generation and energy demand of the users. This chapter is based on [Mediwaththe et al., 2016b, Mediwaththe et al., 2016a] and some additional analysis and numerical results.

5. In Chapter 6, we develop a hierarchical energy trading system between the CES operator and the residential PV energy users while considering users' non-ideal participating time decisions with the use of prospect theory as presented in [Mediwaththe and Smith, 2016a]. We show that with time-varying subsets of active participating users depending on their participating time decisions, the energy trading system attains a unique Stackelberg equilibrium where the CES operator maximises revenue while the users minimise energy costs. Furthermore, the benefits of the energy trading system are robust to users' non-ideal participating time decisions.

6. In Chapter 7, we study an EV charging competition among multiple EV aggregators in a coordinated EV charging system while accounting for potential non-ideal actions of the aggregators as presented in [Mediwaththe and Smith, 2016b]. We model the aggregators' coordinated EV charging competition as a two-stage non-cooperative game and show that there exists a subgame perfect ϵ-Nash equilibrium when the game is played with either ideal, or non-ideal, actions of the aggregators. Furthermore, through an extensive performance analysis, we show that the benefits of the coordinated EV charging system are resilient to non-ideal actions taken by the aggregators.

1.3 Challenges in Demand-Side Management

Demand-side management requires power system operators to deal with energy demand- and supply-side simultaneously, creating numerous challenges for the system operators. The contributions of this thesis primarily intend to address the following key challenges related to demand-side management.

- *Understanding heterogenous and complex interactions among smart grid players*
  The operation of smart grid has become user-centric with the introduction of consumer-driven applications such as demand-side management. Demand-side management requires energy consumers to subscribe energy management programs so that utility companies can modulate peak energy demand that compromises the grid stability. In such a paradigm, studying complex and heterogeneous interactions among different participating entities, such as energy consumers, utility companies, and ancillary service providers, with different goals has been one of the intricate challenges faced by smart grid operators. This challenge has become profound in the context of demand-side management that intends to incorporate consumer-owned distributed energy resources. In the conventional power grid, the popular practice is to define a centralised objective function to optimise system-wide parameters [Saad et al., 2012]. However, with the use of consumer-owned energy devices, centralised approaches would be less practical as their optimal operation requires users to reveal private energy information to the controller. Alternatively, decentralised methods such as energy management based on game theory can be used to achieve system-wide objectives while distributing the decision-making to individuals and taking into account individuals' complex behaviour.

- *Challenges to exploit consumer-owned energy resources*
  The extensive growth of behind-the-meter PV power generation capabilities in residential areas provides a promising means for small-scale demand-side management. However, due to the intermittent and uncontrollable nature of PV power generation and due to the mismatch between consumer demand and PV power generation profiles, significant amount of PV power can be wasted unless surplus PV energy is properly stored for later use. Energy storage devices can facilitate the utilisation of PV energy generation for effective demand-side management by storing surplus energy that can be used to supply energy demand during peak hours. To this end, consumer-owned energy storage devices, electric vehicle battery storage devices or centrally located CES devices can be integrated with demand-side management to regulate peak energy demand of residential communities. There is an abundant literature that has studied effective methods to exploit distributed energy generation at consumer premises where users possibly own energy storage devices [Justo et al., 2013, Guerrero et al., 2013, Atzeni et al., 2014, Atzeni et al., 2013a, Maity and Rao, 2010]. However, there might be situations where energy consumers are not interested

to store energy for future use using local energy storage devices due to cost of energy storage devices. Furthermore, users would potentially like to use PV energy immediately as it is generated [Tushar et al., 2015]. Such scenarios prompt challenges to derive real benefits from consumer-owned PV energy generation and therefore, requires alternative methods to utilise consumer-owned PV energy generation for effective demand-side management while producing benefits to energy consumers.

- *Prioritizing user comfort in demand response*
  Demand response programs are usually intended to change energy consumption profiles of end-users from their regular energy consumption patterns using time-varying energy price signals. Demand response also includes intentional energy consumption reductions by utility companies, commonly known as direct load control, that alter timing of energy consumption or instantaneous energy demand of users [Mohsenian-Rad et al., 2010]. In these cases, energy consumers will experience discomfort due to reshaping their energy activities and this, consequently, decreases adoption rate of demand response programs by users. Therefore, it is of significant interest to devise energy management programs that could take into account user comfort while maintaining the system reliability. To this end, demand-side management that utilises onsite energy generation from consumer-owned distributed energy resources has shown to provide viable energy management frameworks where users may not experience modification to their regular energy consumption patterns [Albadi and El-Saadany, 2007]. In this regard, only few works related to demand-side management literature have focused on utilising energy from onsite generation without reshaping consumers' demand profiles [Atzeni et al., 2013a, Atzeni et al., 2013b]. Lack of investigations of demand-side management that utilises renewable energy without changing user energy consumption profiles incites developing novel energy management methods to exploit renewable energy without modifying users' energy demand profiles.

- *Non-ideal consumer behaviour in demand-side management*
  Successful demand-side management requires active participation of energy consumers to achieve optimal benefits. Perpetuating active consumer participation is one of the cumbersome tasks faced by smart grid system designers since users may not perform consistent behaviour over time [Haney et al., 2011]. Non-ideal, realistic user behaviour could potentially deprive the anticipated outcomes and lead system failures. Therefore, modelling realistic consumer actions and studying their potential impacts on benefits of demand-side management would ease the implementation of successful demand-side management strategies.

1.4 List of Publications

[R1] [Mediwaththe et al., 2016b] C. P. Mediwaththe, E. R. Stephens, D. B. Smith and A. Mahanti, "A Dynamic Game for Electricity Load Management in Neighborhood Area Networks," in *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1329-1336, May 2016.

[R2] [Mediwaththe et al., 2016a] C. P. Mediwaththe, E. R. Stephens, D. B. Smith and A. Mahanti, " Competitive Energy Trading Framework for Demand-side Management in Neighborhood Area Networks," accepted to appear in *IEEE Transactions on Smart Grid*, 2016.

[R3] [Mediwaththe and Smith, 2016a] C. P. Mediwaththe and D. B. Smith, "Game-theoretic Demand-side Management Robust to Non-Ideal Consumer Behavior in Smart Grid," in *Proc. IEEE International Symposium on Industrial Electronics* (ISIE), Santa Clara, June, 2016.

[R4] [Mediwaththe and Smith, 2016b] C. P. Mediwaththe and D. B. Smith, " Game-Theoretic Electric Vehicle Charging Management Resilient to Non-Ideal User Behavior," submitted to *Applied Energy*, 2016.

The related thesis chapters and the publications are given in Table 1.1.

1.5 Thesis Outline

The thesis is organised as follows.

- Chapter 2 presents a summary of theoretical background used in the thesis followed by a comprehensive literature review on demand-side management.
- Chapter 3 presents the decentralised energy trading system between a CES device and residential PV energy users where the users' autonomy to minimise energy costs is studied using a non-cooperative repeated game. The chapter concludes with an

Table 1.1: Thesis chapters and corresponding publications

Thesis Chapter	Publication
Chapter 3	[R1]
Chapter 4	[R2]
Chapter 5	[R1, R2]
Chapter 6	[R3]
Chapter 7	[R4]

extensive simulation analysis that demonstrates the performance of the proposed system.

- Chapter 4 explains the development of the fully-competitive hierarchical energy trading system between the CES operator and energy users. The chapter describes the non-cooperative Stakelberg game between the CES operator and users while discussing its properties. The numerical performance comparison between the proposed energy trading system and two other potential energy systems with different CES operator models is demonstrated.

- Chapter 5 presents the numerical performance analysis that is carried out to analyse the impacts of PV energy generation and user demand forecast errors on the proposed energy trading systems in Chapter 3 and Chapter 4. First, the performance of the energy trading systems is investigated by introducing errors into the day-ahead forecasted energy profiles. Then the simulations are extended to investigate impacts of energy forecast errors that could arise with continuous updates to predicted PV energy and demand profiles.

- Chapter 6 explains the development of the hierarchical energy trading system considering non-ideal participation behaviour of users. Here, the bi-level energy trading system is developed similar to the fully-competitive energy trading system in Chapter 4. The non-ideal actions are modelled using a prospect-theoretic approach. The performance of the energy trading system, when the users are non-ideal, is compared with the system outcomes obtained under expected utility theory that is the conventional game-theoretic approach.

- Chapter 7 presents the investigation of the EV charging competition among EV aggregators in a coordinated EV charging system while considering the aggregators' non-ideal actions. First, the system models in the coordinated EV charging strategy including EV charging costs are explained. Next, the non-cooperative two-stage game among the aggregators is developed while discussing its properties. Then, the analysis of the solutions of the game when the aggregators adopt non-ideal actions is elaborated based on prospect theory. Finally, a numerical case study is given to demonstrate the impacts on the coordinated EV charging benefits when the aggregators' actions are non-ideal.

- In Chapter 8, a summary of the significant research findings in this thesis and potential future extensions to this research are discussed.

Chapter 2

Theoretical Background and Literature Review

Demand-side management has been generally seen as a complex task since it involves interactions among heterogenous groups such as energy consumers and utility companies. In this thesis, the interactions among the players involved in the energy trading frameworks are studied using non-cooperative game theory and prospect theory. The first half of this chapter summarises important terminology of game theory and prospect theory, that we use in the thesis, by presenting fundamental concepts and definitions related to the two theories. The second half of this chapter provides a comprehensive literature review related to demand-side management in smart grid. In particular, starting from a broad discussion on existing demand-side management techniques, we subsequently investigate existing mechanisms to utilise energy from distributed energy resources for demand-side management under two categories: centralised control and decentralised control. Then, we illustrate numerous applications of game theory as a decentralised optimisation tool in demand-side management literature. Finally, an up-to-date investigation on consumer behaviour modelling related to demand-side management is given.

2.1 Game theory

Game theory is a mathematical tool and conceptual framework that can be used to study complex, self-interested interactions among rational players. The application of game theory has exceedingly grown in numerous disciplines such as political science, economics, sociology, psychology, and even in energy related applications in smart grid.

Game theory can be categorised into two branches: non-cooperative game theory and cooperative game theory (coalitional game theory). Non-cooperative game theory essentially studies the settings where multiple payoff-maximising players, who have partially or totally contradictory interests over the system and/or personal outcomes, interact with each other. Moreover, in non-cooperative game theory, users act without any coordination or communication with their opponents and the fundamental modelling unit is the individual considering their beliefs, actions, and preferences [Brown and Shoham, 2008]. On the contrary, cooperative game theory could be applied to situations where communication among players is enabled, and the fundamental modelling unit in cooperative game theory is the set of players. In this thesis, we employ insights from non-cooperative game theory to model and study coordination among independent rational users in energy trading frameworks.

2.1.1 Non-cooperative Games

A non-cooperative game is defined as a combination of players, actions, strategies, and outcomes/payoffs. In this context, players are the entities or users that engage in a specific game, and actions are defined as the possible moves available to the players in the game. Strategies define the complete plan of how each player chooses their actions in the given circumstances. For example, if a user has to decide what to do when operating the air conditioner in his room, and the available options are to switch on and switch off, then a possible strategy would be: "if the temperature inside the room is below $25\,°C$, then I will switch off the air conditioner, otherwise I will switch on the air conditioner". Finally, an outcome/payoff of a non-cooperative game delineates the level of happiness that the player gains through performing an action.

There are two alternative methods to represent non-cooperative games: extensive-form games and normal form games. In general, extensive form, which is also known as tree from [Brown and Shoham, 2008], involves the notions of time and sequence that users move in a particular game. Therefore, extensive forms of non-cooperative games do not always assume that users act simultaneously. The extensive form of a game describes

1. The set of players
2. Times when players move and their choices at each move
3. What information available to each player when they move
4. Payoffs for all players in every combination of moves

Fig. 2.1 shows an illustration of a two-player game represented in extensive form (tree form).

The normal form, which is also known as strategic form, is the most straightforward representation of non-cooperative games. In this thesis, we focus on normal form representations of non-cooperative games. The normal form of a game identifies the set of

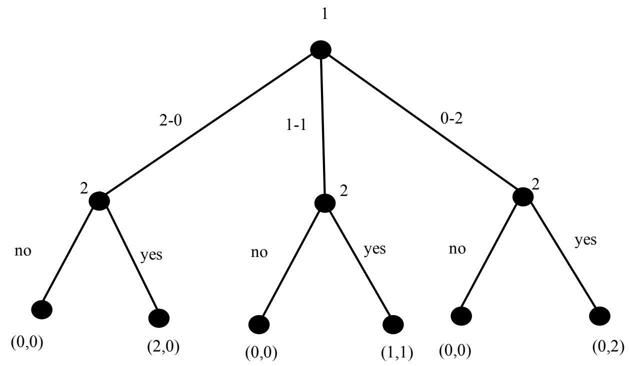

Fig. 2.1: Extensive form illustration of a game.

players, strategies available to each player, and payoffs. Formally, a non-cooperative game in its normal form is defined as a tuple $\langle \mathcal{V},\ \mathcal{A},\ J \rangle$ where [Brown and Shoham, 2008]

- $\mathcal{V}$ is the set of players and $|\mathcal{V}| = V$;
- $\mathcal{A}$ is the set of actions available to the players $\mathcal{V}$ and is given by $\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_V$ where $\mathcal{A}_i$ is the set of all actions available to player $i \in \mathcal{V}$;
- $J = (J_1 \times \cdots \times J_V)$ where J_i is defined as a utility function for user i such that $J_i : \mathcal{A} \rightarrow \mathbb{R}$.

The most common way to represent the normal form of a game is through an n-dimensional matrix [Brown and Shoham, 2008]. Fig. 2.2 illustrates the normal form of the canonical two-player prisoner's dilemma using a 2×2 matrix. In this game, the actions available to each player are confess (C) and deny (D) the crime. In Fig. 2.2, each label corresponds to rows and columns denotes the possible actions for the player 1 and player 2, respectively. The costs, i.e., negative of payoffs, for each possible combination of the actions are given inside the boxes. Here, the costs are the time that the prisoners have

	C	D
C	3,3	1,4
D	4,1	2,2

Fig. 2.2: Prisonner's Dilemma.

to spend in jail. For example, if both prisoners confess the crime, then they both have to spend 3 years in jail .

In non-cooperative game theory, strategies are identified according to two categories: pure (deterministic) strategies and mixed strategies. Pure strategies are defined when users play single actions, whereas mixed strategies are used to explain the situations when the players randomise their actions by using some probability distribution over the sets of available strategies. Moreover, a pure strategy is regarded as a special occurrence of a mixed strategy where a particular action is played with probability 1 [Brown and Shoham, 2008]. The formal definition for a mixed strategy can be given as follows.

Definition 1. *Given a non-cooperative game* $\langle \mathcal{V},\ \mathcal{A},\ J \rangle$, *the set of mixed strategies for player* $i \in \mathcal{V}$ *is defined as* $P_i = p(\mathcal{A}_i)$ *where* $p(\mathcal{A}_i)$ *represents the set of all probability distributions over the action set* $\mathcal{A}_i$.

2.1.2 Static Games versus Dynamic Games

In non-cooperative game theory, there are two types of games: static games and dynamic games. In static games, players make decisions without knowing the actions of their opponents. This does not necessarily mean that all players make decisions simultaneously [Basar and Olsder, 1999]. In a static game, players' order of decisions can be irrelevant. If the players in a game act only once and independent on others' actions, then the game is called a static game [Basar and Olsder, 1999]. For example, prisoner's dilemma in Fig. 2.2 can be considered as a static game when the prisoners are allowed to act once and choose either to confess or to deny the crime without knowing opponent's decision.

In contrast to static games, the order of movements of players are important in dynamic games [Basar and Olsder, 1999]. In a dynamic game, at least one user adopts a strategy that depends on the history of actions. A game can be dynamic mainly due to two reasons [Basar and Olsder, 1999]. The first is that the interactions among players can be dynamic, and they can observe their opponents' actions before making decisions. Secondly, a game can be dynamic if a one-off game is played many times, and the players can observe the results of the games played in the past before playing the current game. More importantly, in dynamic games, some players can reason about their decisions depending on what their opponents have done before.

2.1.3 Nash Equilibrium in Non-cooperative Game Theory

In non-cooperative games, best response is one of the commonly used terms and is usually defined as the optimal strategy that a user can adopt in response to their opponents' strategies. Let us define a strategy profile $\boldsymbol{b}_{-i} = (b_1, \cdots, b_{i-1}, b_{i+1}, \cdots, b_V)$ as the strategy profile of all players without the strategy b_i of player i. Then the overall strategy profile of all players can be denoted as $\boldsymbol{b} = (\boldsymbol{b}_{-i}, b_i)$. Using these notations, we can define a best response of user i as follows [Brown and Shoham, 2008].

Definition 2. *The best response of player i to a strategy profile $\boldsymbol{b}_{-i}$ is a mixed strategy $\tilde{b}_i \in P_i$ if it satisfies $J_i(\tilde{b}_i, \boldsymbol{b}_{-i}) \geq J_i(b_i, \boldsymbol{b}_{-i}),\ \forall b_i \in P_i$.*

Leveraging the idea of best response, Nash equilibrium forms one of the important solution concepts in non-cooperative game theory. The formal definition of a Nash equilibrium can be given as follows [Brown and Shoham, 2008].

Definition 3. *A strategy profile $\boldsymbol{b}^* = (b_1^*, \cdots, b_V^*)$ is a Nash equilibrium if each users' strategy b_i^* is a best response to $\boldsymbol{b}_{-i}^*$.*

The definition of a Nash equilibrium indicates that none of the players cannot find a better solution to maximise payoff rather than their strategy at the Nash equilibrium while other players play their optimal strategies determined at the Nash equilibrium. In a non-cooperative games with finite number of action profiles and players always have at least one mixed strategy Nash equilibrium. However, there is no guarantee that every finite non-cooperative game has a Nash equilibrium in pure strategy [Nash, 1951].

2.1.4 Pareto Optimality and Nash equilibrium

Another important term which is associated with game theory is Pareto optimality. A strategy profile in a non-cooperative game is Pareto optimal when it is impossible to exist another strategy profile that can increase any one users' payoff without decreasing payoff of at least one other user.

Definition 4. *When $P = P_1 \times \cdots \times P_i \times \cdots \times P_V$, a strategy profile $\boldsymbol{b} \in P$ is Pareto optimal when it is impossible to obtain $\boldsymbol{b}^{'} \in P$ such that $J_i(\boldsymbol{b}) \leq J_i(\boldsymbol{b}^{'}),\ \forall i \in \mathcal{V}$ and $J_i(\boldsymbol{b}) < J_i(\boldsymbol{b}^{'})$ for some $i \in \mathcal{V}$.*

In a non-cooperative game, a Nash equilibrium does not always need to be Pareto optimal. Nash equilibrium quantifies the efficiency of the solution of a game from an individual's perspective, whereas Pareto optimality gives intuition to an outside viewer whether the final solution is efficient [Brown and Shoham, 2008]. One of the simplest examples to understand the difference between Pareto optimality and Nash equilibrium is the non-cooperative prisoner's dilemma (see Fig. 2.2) where the unique Nash equilibrium is not Pareto optimal. In particular, its unique Nash equilibrium (C, C) is not Pareto optimal because the two prisoners can be better off by choosing the strategy profile (D, D).

2.1.5 Imperfect Information in Game Theory

Imperfect information is regarded as an important notion in non-cooperative game theory. Generally, non-cooperative games can be studied under two classes: games with perfect information and games with imperfection information. In games with perfect information, players have the perfect knowledge of the state of the game including all players' actions, their payoffs, and even about the environment [Brown and Shoham, 2008]. For example, playing chess can be considered as a game with perfect information. However, in many situations, players have partial or no knowledge about the other players' actions or the environment. Non-cooperative games studied under such situations are known as games with imperfect information [Brown and Shoham, 2008]. Traditionally, imperfect information in games has been modelled with respect to actions of players which implies that players cannot observe the actions of their opponents while making their own decisions. For example, simultaneously played prisoner's dilemma (see Fig. 2.2) can be regarded as a good example for a non-cooperative game with imperfect information with regards to players' actions where prisoners cannot observe their opponent's choice at the time he selects an action. The concept of imperfect information in game theory could also include imperfect information with respect to the environment or nature. In this thesis, the non-cooperative game-theoretic energy trading systems will be analysed under imperfect information with regard to environment by considering potential energy demand and photovoltaic energy forecast errors.

2.2 Prospect Theory

The main assumption of game theory is that players are rational when making their strategic decisions and are satisfied as long as their payoffs in the game are maximised. In an environment where multiple users interact with each other, players possibly face uncertainty and risk about the outcomes or decisions they make. In smart grid, this situation is more likely to arise as it motivates interactions among diverse entities and complex systems to achieve various aspects in smart grid. For example, in a demand-side management program that encourages customers to shift their energy activities to non-peak hours, some customers may not want to change their activities even if they receive billing discounts. Such a paradigm would often create an uncertain environment for other users to make their decisions about changing the energy activities to receive their anticipated cost benefits. This uncertainty might demotivate some energy consumers to participate in the energy management program leading to failures in the expected outcomes. Moreover, some may perform actions that are not completely rational as perceived by classical game theory. Motivated by such conditions, one of the central themes of this thesis is to look at non-ideal behaviour of energy customers and its potential impacts on the proposed game-theoretic energy trading systems using prospect theory.

Prospect theory is one of the important analytical techniques that is used to investigate and model user behaviour, which contradicts the underlying rationality assumption in classical game theory. Fundamentally, it models how people, in the real world, make choices between prospects. According to prospect theory, a prospect is defined as follows [Kahneman and Tversky, 1979].

Definition 5. *A prospect is defined as a contract* $(f_1, l_1; \cdots ; f_j, l_j; \cdots ; f_K, l_K)$ *that produces outcome* f_j *with a certain probability* l_j *and* $l_1 + \cdots + l_j + \cdots + l_K = 1$.

In demand-side management, the actions of customers may vary with time leading to an uncertain environment for users to optimise their individual objectives by reasoning about their neighbours' actions. In this scenario, the analytical platform of prospect theory provides useful tools to model how users perceive their opponents' actions when determining their optimal reactions.

2.2.1 Weighting Approach in Prospect Theory

Weighting approach is one of the central tools of prospect theory that primarily assigns weights, based on a weighting function, to the probabilities of actions played by users. In the context of classical game theory, the rationality assumption mainly relies on the fact that users are objective and hence, all users adopt the realised objective probabilities of opponents' actions to maximise their personal payoffs. However, empirical evidence from many social studies has shown that people tend to be subjective by underweighting high probability events and overweighting low probability events when they face risk and uncertainty in strategic decision making. In prospect theory, this subjective behaviour is commonly dealt with weighting approach and to this end, weighting functions are used to approximate subjective user behaviour. One of the widely used wighting function is the Prelec function [Prelec, 1998], which better represents much of the available empirical evidence of user behaviour [Al-Nowaihi and Dhami, 2006]. According to Prelec function, the weighting of the event with a probability u, $w(u)$, is given by

$$w(u) = \exp(-(-\ln u)^{\kappa}) \tag{2.1}$$

where κ is a weighting parameter that quantifies the distortion between subjective and objective evaluations and $0 \leq \kappa < 1$. Fig. 2.3 shows the variation between objective probabilities u, i.e., the real probabilities, and the subjective probabilities $w(u)$ for different κ values. Here, player becomes more subjective when κ moves towards 0. On the other hand, when $\kappa = 1$, player behaves objectively and represents the classical game-theoretic approach, i.e., expected utility theory.

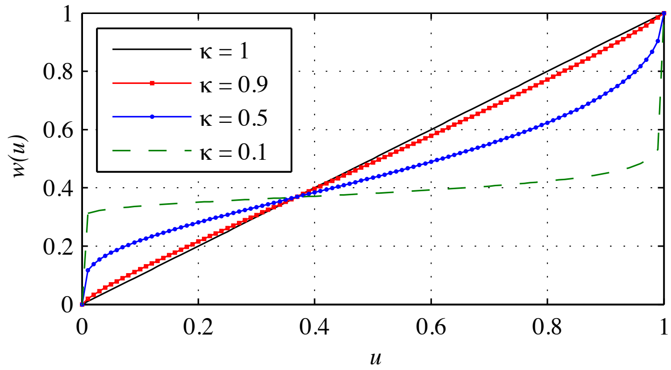

Fig. 2.3: Variation between objective and subjective probabilities as per the Prelec function with different κ.

2.3 Literature Review

2.3.1 Demand-Side Management in Smart Grid

Demand-side management refers to managing energy consumption of electricity users to reduce the discrepancy between electricity supply and demand. In general, shaping of energy consumption profiles of users is performed by using six different ways, which are summarised in Fig. 2.4 [Logenthiran et al., 2012]. One option to achieve the adjustment of users' energy consumption profiles is through direct load control where utility companies remotely control electric appliances at consumer premises according to an agreement between users and the utility. Alternatively, numerous smart pricing techniques are adopted by utility companies to motivate users to voluntarily modify their own energy activities such that their energy costs are reduced [Samadi et al., 2015].

In literature, load shifting has been the popular approach that takes the advantage of controllable electric appliances at consumer premises to shape users' energy consumption

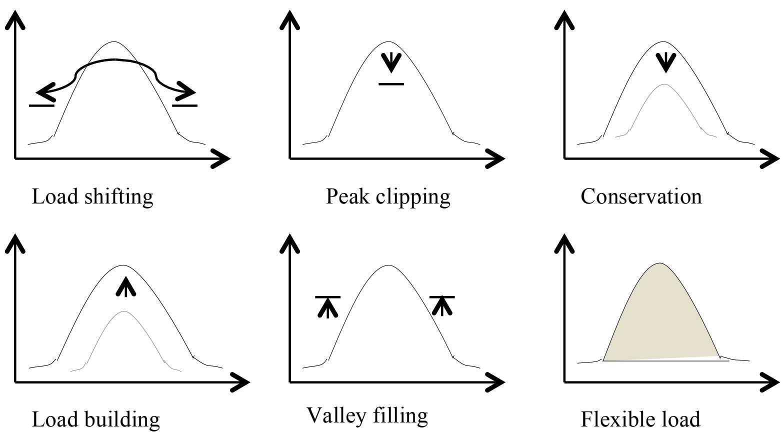

Fig. 2.4: Standard techniques of demand-side management [Logenthiran et al., 2012].

profiles across time. In [Logenthiran et al., 2012], a load shifting approach is proposed for demand-side management based on a heuristic evolutionary algorithm. At single household level, [Adika and Wang, 2014a] studies an autonomous electric appliance scheduling approach by developing a smart scheduler that use devices' time of use probabilities and real time energy prices. The decentralised agent-based approach in [Pournaras et al., 2014] explores optimal demand planning of energy consumers, and the method reduces discomfort for energy users due to load shifting or load adjustment. In the distributed electric appliance scheduling method in [Chavali et al., 2014], users determine optimal start times to operate their energy devices according to day-ahead determined energy prices of utility.

In [Ma et al., 2016], a residential load scheduling approach is proposed to increase cost efficiency of energy consumption of users, and a real time energy pricing method is proposed to influence the residential energy users to schedule their energy consumption. Using a two-level hierarchical method, [Vivekananthan et al., 2014] studies a demand response program for residential energy users where the users are rewarded for their level of demand shifts and voltage improvements due to shifting energy demands. In [Nguyen and Le, 2014], a study of minimising energy cost and user discomfort in a load shifting approach proposed for home energy consumption scheduling and electric vehicle charging scheduling is presented. The optimisation framework considers the electric vehicle energy storage devices as dynamic energy storage facility for demand-side management while taking the household occupancy into account. An optimal demand bidding mechanism for energy management in hotels is proposed in [Tarasak et al., 2014] such that the expected reward for energy saving is maximised. In general, demand bidding programs influence large energy customers such as hotels and shopping malls to bid for energy consumption reductions and the customers are recompensed if their energy reductions satisfy the energy requirement posed by the utility.

Considering the stochastic nature of electricity prices, photovoltaic (PV) energy generation, and energy loads, [Wu et al., 2014] investigates a real-time demand response mechanism to schedule household appliances. The paper uses conditional value-at-risk method to explore the trade-off between energy costs and uncertainty risk of electricity prices. A preemptive energy management method for commercial buildings is investigated in [Sivaneasan et al., 2015] to maintain the energy demand of the building below the demand capacity limit of utility. The method uses precautionary signals to prevent the building from violating the capacity constraints of the utility. A home energy management controller is proposed in [Althaher et al., 2015] that optimally controls the energy demand of deferrable loads, curtailable loads, and thermal loads of a household to reduce energy cost of users whilst minimising users' discomfort due to energy curtailment. The demand-side management method in [Yao et al., 2016] reduces the reverse power flow of PV energy, due to excessive PV generation, through an energy consumption scheduling of deferrable loads. The paper uses a stochastic programming method to consider uncertainty of PV energy generation. Customer engagement plans for demand response through load scheduling are investigated in [Hassan et al., 2015] such that users can select suitable plans according to their requirements. Using a practical testbed, [Li et al., 2015] verifies the efficiency of two demand response customer engagement plans, namely, green savvy and green aware plan.

In [Qela and Mouftah, 2014], a peak load curtailment method using fuzzy logic approach is proposed to initiate optimal peak load reduction set points in cities. In [Graditi et al., 2015], an optimal energy management method for distribution power networks is investigated where utility determines the optimal dispatch signals for energy generation units and energy consumption set points for energy users. A direct load control method where utility controls the energy consumption of users with minimum discomfort to obtain optimal demand-side management is studied in [Ramanathan and Vittal, 2008]. The direct load control method in [Ruiz et al., 2009] controls energy schedules of controllable energy devices owned by a large number of energy consumers in a virtual power plant consists of distributed energy resources such as storage, generation, and flexible demand.

Various smart price-based demand-side management methods have been studied in literature. Generally speaking, these techniques motivate energy users to adjust their energy consumption patterns in response to time-varying energy prices imposed by utility companies. A smart pricing method to influence consumers to adjust their energy consumption across time is proposed in [Ma et al., 2014] such that the social benefit of energy consumers is maximised. The method also prevents untruthful information exchange between energy users and provider. In [Li et al., 2014], a computational method to compare different price-responsive demand response strategies for residential customers is studied by modelling home energy consumption using a regression technique. Real time price responsive demand-side management for heating, ventilation, and air-conditioning is proposed in [Yoon et al., 2014] to minimise energy cost and thermal discomfort of a household. The one-leader multiple-follower Stackelberg game in [Yu and Hong, 2016a] studies a real time price responsive demand-side management for optimal load scheduling of energy devices. In [Vivekananthan et al., 2015], an algorithm for home energy management schedular that operates under real-time pricing environment is proposed such that the algorithm minimises energy cost of a household by considering uncertainties of price and real-time prices.

Demand-side management has become prominent element to maintain power system stability under excessive energy demand of ever-growing electric vehicles. Optimal load scheduling approaches for plug-in hybrid electric vehicles to mitigate over-loading of low-voltage distribution transformers due to excessive energy consumption are investigated in [Mou et al., 2015]. Optimal charging load scheduling of a fleet of plug-in electric hybrid electric vehicles is proposed in [Craemer et al., 2014] by using a dual coordination mechanism that coordinates market operation and real time operation of plug-in electric hybrid vehicles charging while minimising the message exchange between the aggregator and vehicles. The hierarchical interaction between an electric vehicle aggregator and electric vehicle owners is considered in [Sarker et al., 2015] where the aggregator determines the energy price that maximises its profit while the electric vehicle owners schedule their energy consumption in response to the price signal of the aggregator. In doing so, the method mitigates overload conditions of distribution network. Considering the randomness of availability of electric vehicles, [Rassaei et al., 2015] proposes an optimal demand response strategy for electric vehicle charging at households.

2.3.2 Demand-Side Management with Distributed Energy Resources

Rapid fluctuations and the uncontrollable nature of renewable energy generation, such as wind and solar, create imbalance between energy supply and demand and hence, impose challenges for nominal power system operation including voltage and frequency instabilities. Combined with demand-side management, energy storage devices provide viable solutions to mitigate power quality issues of renewable energy generation [Heussen et al., 2012]. In particular, energy storage devices can be used to store renewable energy when the generation is excessive, which can then be dispatched when the electricity demand is high.

The operation and control methodologies for a grid-scale battery energy storage system are proposed in [Hill et al., 2012] to alleviate the negative impacts of PV power generation such as frequency and voltage instabilities to improve the efficiency of overall power distribution. The proposed optimisation in [Marnay et al., 2008] selects the optimal combination of distributed energy resources such as generators and energy storage devices in commercial buildings such that cost savings and carbon reductions are maximised. The design and operation aspects of distributed battery micro-storage systems in a deregulated electricity market are investigated in [Hussein et al., 2012]. In this regard, system design architecture, system sizing, and economic aspects are studied with and without PV energy generation. Existing literature related to controlling distributed energy resources to achieve system-wide objectives can be mainly classified into centralised and decentralised approaches.

2.3.2.1 Centralised Control Methods for Distributed Energy Resources

In general, centralised approaches for controlling distributed energy resources require a centralised authority to determine the energy strategies for local resources. Moreover, the central controller requires power information of each distributed resources to obtain optimal operation. Fig. 2.5 illustrates an example of a microgrid with distributed energy resources that is controlled by a centralised controller. A centralised method to control the dispatching strategies of distributed energy storage devices is explored in [Celli et al., 2012] such that the proposed system achieves the optimal power flow among microgrid elements and minimises costs of energy losses. With the use of model predictive control, [Xie and Ilic, 2009] solves a centralised multi-objective optimisation problem that minimises the energy generation cost to satisfy demand by utilising energy form renewable resources. The multi-objective optimisation also studies the trade-off between efficiency and environmental impact of power generation. The optimisation in [Sugihara et al., 2013] solves the voltage fluctuation problem of distribution power network due to high penetration of PV energy generation, and the proposed approach adopts a centralised method where the distributed network controller controls the output energy flows of energy storage devices owned by commercial energy users. In return, the customers are subsidised by the network controller in order to motivate the users to install energy storage devices with more capacity.

To support the increasing demand of plug-in electric vehicles in residential distribution networks, [Arghandeh et al., 2012] proposes a centralised energy management system with the use of distributed energy storage devices connected to the distribution transformer. In [Sortomme and El-Sharkawi, 2009], the problem of generation cost minimisation of

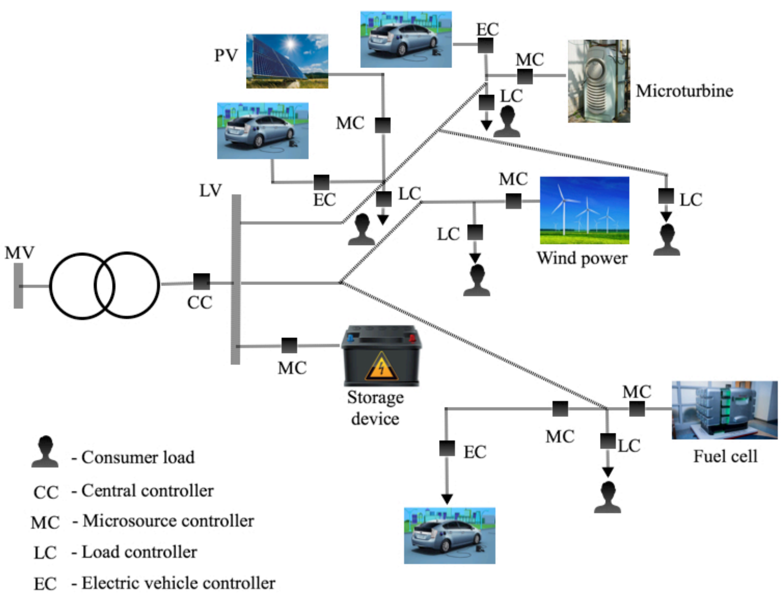

Fig. 2.5: A microgrid controlled by a centralised controller.

multiple microgrids is considered where the distributed energy storages are utilised to perform the optimal energy management. In [Marano et al., 2012], using a dynamic programming method, an optimal load management method for a hybrid power plant consists of compressed air energy storage, wind farm, and a photovoltaic power plant is proposed. At single-user level, [Matallanas et al., 2012] explores an optimal residential load shifting demand-side management framework with household-distributed PV energy generation and energy storage device to maximise user's self-consumption. An optimal sizing method for energy storage systems is proposed in [Abbey and Joos, 2009] to take the full advantage of wind power such that the diesel fuel consumption is reduced. The smart energy management system in [Chen et al., 2011a] optimally coordinates the power production of distributed energy resources and dispatch commands for energy storage devices to minimise the operational costs of a microgrid. The feasibility of small-scale energy storage devices to balance energy supply and demand with high penetration of intermittent renewable energy generation is considered in [Heussen et al., 2012]. This work presents a unified power node modelling framework to facilitate energy storage devices as well as other energy elements with different controllability levels and validates the framework through a centralised optimisation problem that determines optimal operating set points for distributed energy resources.

2.3.2.2 Decentralised Control Methods for Distributed Energy Resources

The majority of existing literature based on decentralised control techniques for distributed energy resources exploit autonomous behaviour of local controllers at distributed energy resources such that global and local objectives are optimised. An example of a microgrid that is controlled in decentralised way is given in Fig. 2.6 [Colson and Nehrir, 2011].

The cooperative control of distributed energy resources proposed in [Caldognetto et al., 2014] takes the full advantage of the power control ability of renewable resources and energy storage units to maximise energy efficiency and voltage stability of a microgrid. The cooperative control method based on token ring approach in [Tenti et al., 2010] minimises distribution losses in a residential microgrid consists of renewable energy generators and energy storage devices. The decentralised nature of the method enables cross communication among electronic power processors at each local energy source to increase the system efficiency without a centralised controller. In [Hadjsaid et al., 2009], a decentralised control-based experimental platform is studied to enable the operation of electrical distribution systems under high penetration of renewable energy. A review of multi-agent systems for controlling distributed energy resources is given in [Roche et al., 2010], and an agent-based decentralised control method is proposed in [Colson and Nehrir,

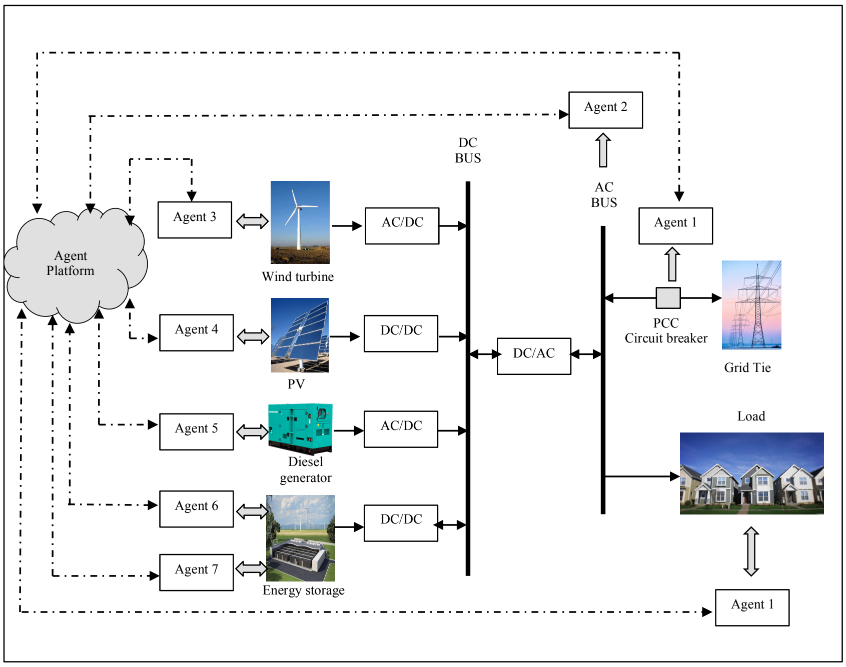

Fig. 2.6: An Agent-based decentralised control structure of a microgrid [Colson and Nehrir, 2011].

2011] to achieve optimal microgrid power management. In [Etemadi et al., 2012b], a decentralised control strategy is studied to enable autonomous response of distributed energy resources in an islanded microgrid such that the system is robust to uncertainties of renewable energy generation and reduces the high-bandwidth communication between the local controllers and the central power management system. Numerical case studies in [Etemadi et al., 2012a] substantiate the robustness of the control strategy in [Etemadi et al., 2012b] by applying the strategy to a microgrid with three types of distributed energy resources represented by a constant dc voltage source, a two-level insulated-gate bipolar transistor voltage source converter, and a three-phase series filter.

Using a three-layer management system, [Horoufiany et al., 2012] proposes a decentralised voltage control method that coordinates distributed energy resources and energy consumption in smart grid. Distribution network automation through a decentralised power flow control method based on graph theory is explored in [Lo and Ansari, 2013]. The method tackles the problems of power imbalances in the network while improving the use of renewable energy generation and reducing data traffic compared to a centralised energy management system. The proposed methodology in [Kinjyo et al., 2012] controls the distributed controllable loads such as electric vehicles and heat pump water heaters to mitigate the voltage and frequency fluctuations due to renewable energy generation. The multi-agent system in [Collins et al., 2013] performs distributed decision making among energy resources such that the power system voltages are within safe operating regions. The problem of active power curtailment to prevent voltage fluctuations on the grid due to PV energy generation is addressed in [Reeves et al., 2013] by proposing a distributed communication-based method. In [Etemadi et al., 2014], autonomous mode of operation of a microgrid is considered such that it can maintain the optimal frequency under disturbance and achieve accurate power sharing among microgrid elements under impedance uncertainties. A detailed literature review on decentralised control techniques for microgrids is presented in [Yazdanian and Mehrizi-Sani, 2014]. Based on a constraint satisfaction algorithm, [Luo et al., 2015] studies a hybrid distributed control algorithm to minimise thermal overload in distributed power network.

A flow invariant-based energy management approach is proposed in [Gamage et al., 2015] for efficient and scalable power flow management within a microgrid, and the method is formulated as decentralised control among base units in the microgrid. For the purpose of mitigating over-voltage and under-voltage problems in a microgrid, optimal decentralised energy management of distributed energy resources using gossip control-based algorithm is investigated in [Koukoula and Hatziargyriou, 2015]. In [Javaid et al., 2016], the concept of power flow colouring that attaches unique identification to each power flow between a pair of energy source and load is used for versatile decentralised power flow control among distributed energy resources in a nano-grid. In [Rongali et al., 2016], a decentralised approach for controlling dispatch commands for distributed energy resources is investigated such that the voltage instability of the power grid due to high penetration of PV energy is minimised.

Optimal decentralised coordination among distributed energy resources in a microgrid is studied in [Papadaskalopoulos et al., 2014] using a Lagrangian relaxation method. The method optimally controls both active and reactive power flows within the microgrid and eliminates creating rebound peaks in energy demand. Another decentralised control method for microgrid components is proposed in [Shah et al., 2011] to exploit the frequency fluctuations in the microgrid, due to distributed energy resources such as renewable energy generation, to balance the active power generation and the energy consumption within the microgrid. A hybrid approach that combines both decentralised and centralised control methods is used in [Lu et al., 2011] to coordinate energy storage devices and demand response in a microgrid such that the use of wind energy is maximised. The energy management system in [Alizadeh et al., 2012] coordinates household energy management systems to alleviate power imbalances due to renewable energy generation, and it has been shown that the decentralised version of the system is more resilient to failures of individual components than the centralised version. Using Lagrange dual decomposition, [Joo and Ilic, 2013] solves the problem of supply and demand balancing between load serving entities and energy consumers, and the algorithm decomposes the global optimisation problem into end users' local problems.

Based on Karush-Kuhn-Tucker conditions of optimality, [Asr and Chow, 2013] investigates a distributed algorithm to optimally control the charging operation of plug-in electric vehicles or plug-in hybrid electric vehicles. A cooperative distributed algorithm for controlling the charging operation of electric vehicles is proposed in [Rahbari-Asr and Chow, 2014] such that the algorithm eliminates the need for a central controller. The method satisfies global and local constraints of charging operations through peer-to-peer communication between electric vehicle charging stations. To address the problem of demand-side load balancing without a central controller, a decentralised method based on BitTorrent-like power swarm approach is proposed in [Titus and Bequette, 2014] to efficiently dispatch distributed energy resources. A fully distributed control algorithm based on consensus optimisation is explored in [Xu and Li, 2015] for optimal power flow planning of distributed energy resources in an islanded microgrid. The algorithm uses an upper level control to determine the reference points of power generation and demand and a lower level control to track the reference power flow points of the associated components. An iterative distributed algorithm based on alternating direction method of multipliers and model predictive control is proposed in [Wang et al., 2015a] to enable optimal decentralised real-time energy management of electric vehicles within a microgrid consists of PV power generation, curtailable loads, and battery storage units. In [Brazier et al., 2015], a decentralised approach using adaptive dynamic clustering is proposed for controlling distributed energy resources such that an optimal supply and demand balance is achieved. In [Barik et al., 2013], a decentralised power sharing algorithm is explored to balance the energy demand and generation within a microgrid with high penetration of wind and PV energy.

Excessive energy generation due to the disparity between renewable energy and demand profiles has led researchers to investigate decentralised energy sharing frameworks. These frameworks enable consumers those who have local energy generation units such as rooftop PV panels to sell surplus energy to the grid or to their neighbours with energy deficits. In [Maity and Rao, 2010], a game-theoretic PV energy sharing framework along with auction theory is proposed for energy management of a small residential area where residential users with PV panels and energy storage devices share surplus PV energy with each other. A cooperative renewable energy exchange game for a small community is investigated in [Alam et al., 2013] to minimise battery usage. The distributed power grid architecture 'LoCal' in [He et al., 2008] enables autonomous energy sharing among distributed energy resources such as energy storage devices, energy loads, and energy generation units to facilitate demand response. In [Zhu et al., 2011], a secure energy routing protocol is proposed for renewable energy sharing among households.

2.3.3 Game Theory in Demand-Side Management

Game theory facilitates exploring decentralised platforms through modelling complex, independent actions of energy consumers in various smart grid contexts. In particular, game theory has been widely applied to study autonomous interactions among participants in demand-side management.

The game-theoretic demand-side management approach in [Yang et al., 2013] investigates optimal time-of-use pricing strategies that minimise costs of utility companies and maximise user satisfaction from energy consumption scheduling as per pricing strategies. The game-theoretic approach in [Fadlullah et al., 2014] studies the interaction between utility and energy consumers where consumers schedule their energy consumption to optimise the difference between energy value and cost such that peak-to-average ratio of the power grid is reduced. Interactions between multiple utility companies and energy consumers is explored in [Chai et al., 2014] using a two-level game. The interactions among utilities are formulated as a non-cooperative game, whereas the interactions among users are studied using an evolutionary game in which they achieve an equilibrium with respect to energy trading strategies. A fair and privacy preserving billing mechanism is proposed in [Baharlouei and Hashemi, 2014] to minimise energy costs of users by shifting their loads across time. The demand-side management in [Atzeni et al., 2014] uses a generalised Nash equilibrium problem to determine day-ahead energy trading strategies of users who own distributed energy resources such as storage devices and controllable energy generators, for example, fuel cells.

The residential energy consumption scheduling in [Deng et al., 2014] is formulated as a coupled-constrained game between users, and the real time version of the proposed method alleviates the impact of price prediction error by adjusting the day-ahead determined consumption schedules. An aggregative game is proposed in [Chen et al., 2014] to investigate a scenario where selfish users compete to minimise their personal energy costs by scheduling their energy consumption profiles. The repeated energy scheduling game in [Song et al., 2014] determines the optimal non-stationary energy scheduling strategies for users from which they can choose different power consumption patterns depending on their individual preferences. In [Kilkki et al., 2015], a game-theoretic approach is proposed to optimise electricity price for electric space heating customers to shift their energy consumption such that the retailer's profit is maximised. In [Kontogiorgos and Papavassilopoulos, 2014], a static Stackelberg game for voluntary load curtailment demand side management is studied where participating users are subsidised for curtailing their energy consumption for a certain period of time. A real time pricing method for load scheduling is examined in [Meng and Zeng, 2014] using a Stackelberg game between an electricity retailer who maximises profit and consumers who maximise energy consumption satisfaction. A user-aware demand-side management approach based on game theory is studied in [Yaagoubi and Mouftah, 2015a] to maximise users' energy cost savings and comfort that depends on their waiting time in an energy consumption scheduling method.

A mutileader-multifollower Stackelberg game is investigated in [Belgana et al., 2015] to maximise utilities' profits and to minimise consumers' energy costs and carbon emissions using an evolutionary algorithm. In [Nekouei et al., 2015], two game-theoretic frameworks are studied where in the first game demand response aggregators make demand reduction bids with the electricity generators. In the second game, mechanism design theory is used to study a load curtailment scheme such that the inconvenience of consumers is minimised. In [Wei et al., 2015], a Stackelberg game is studied to investigate demand response of consumers in response to energy retailer's energy price, whereas linear robust optimisation method is used to study the risk-aversive energy dispatch of the retailer considering uncertainty of energy price of the wholesale energy market. A non-cooperative game-theoretic demand response management is studied in [Belhaiza and Baroudi, 2015] considering the packet errors rates in message exchanging. To schedule energy consumption of residential energy users, [Zhu et al., 2015] presents a potential game-theoretic framework based on mixed integer linear programming that achieves Pareto optimal Nash equilibrium of energy consumption strategies of users.

Demand-side management between smart energy hubs that are multi-carrier energy systems using non-cooperative game theory is studied in [Sheikhi et al., 2015]. A load shifting approach for energy consumers is developed in [Papaioannou et al., 2014] using a serious game. In [Ye et al., 2016], a centralised demand-side management method and a game-theoretic demand-side management method were compared. The paper shows that the game-theoretic approach relieves the information overhead and can preserve consumers' privacy compared to the centralised version. Based on a cooperative game-theoretic demand-side management setting, [O'Brien et al., 2015] proposes a payment distribution method among participating users. A decentralised control algorithm for demand-side management based on cooperative game theory is studied in [Mostafa et al., 2016] where participants' incentive payments increase if their actions improve the system social welfare. A non-cooperative Stackelberg game between multiple energy providers and a large number of energy consumers is proposed in [Maharjan et al., 2016] for energy consumption scheduling and profit maximisation of the participants. In [Yaagoubi and Mouftah, 2015b], the problem of fair billing for energy consumers who participate in demand-side management is explored using a game-theoretic approach. In [Li et al., 2016], an efficient distributed algorithm is proposed to determine the Nash equilibrium of a game-theoretic sparse load shifting method of residential users. The non-cooperative game-theoretic residential demand-side management method in [Mohsenian-Rad et al., 2010] optimally schedules the energy consumption of users and achieves the Nash equilibrium that provides the global minimum of energy costs.

In [Soliman and Leon-Garcia, 2014], a non-cooperative Stackelberg game is proposed between utility and energy users with energy storage devices where users play a non-cooperative game to schedule their energy consumption and energy trading strategies of storage devices. The Stackelberg game has a unique equilibrium between the energy decisions of the utility and users which is also the minimum of the systems' peak-to-average demand ratio problem. In [Adika and Wang, 2014b], a non-cooperative game between energy users is explored to study optimal charging-discharging power profiles of household distributed energy storage devices and electric appliance scheduling. In [Nguyen et al., 2015b], a non-cooperative game among energy users with energy storage devices is proposed to schedule their energy consumption and dispatch commands for storage devices such that utility minimises the distance between instantaneous demand and average demand on the grid.

In [Nguyen et al., 2015a], the problem of voltage control is studied using a Nash bargain-theoretic method where reactive power generation from consumer-owned distributed generation units is utilised to maintain voltage stability. The non-cooperative game in [Atzeni et al., 2013a] studies the minimisation of energy costs of users by determining input/output power transaction strategies for controllable power generators, such as fuel cells and gas turbines, and behind-the-meter energy storage devices. The paper shows that the system achieves effective demand-side management when users reach Nash equilibrium with respect to their energy trading strategies. A model predictive game-theoretic approach, using consumer-owned energy storage devices and PV generation, is proposed in [Stephens et al., 2015] to achieve demand-side management robust to forecasting errors of energy demand and PV energy generation.

In [Bahrami and Parniani, 2014], a demand response method for electric vehicle charging scheduling is studied using a non-cooperative game between vehicle owners. In the method, a stochastic model is used to consider the randomness of starting time of electric vehicle charging and the game between users has a unique Nash equilibrium. In [Xu and Chung, 2015], challenges in a game-theoretic electric vehicle charging system such as inefficiency of Nash equilibria are studied. The paper elaborates an effective solution to mitigate the inefficiencies of Nash equilibria using a central governing scheme. In [Tushar et al., 2012], a Stackelberg game-theoretic electric vehicle charging method is proposed and the method has a unique Stackelberg equilibrium, which is also socially optimal.

In [Sola and Vitetta, 2014], a distributed demand-side management method for load shifting in a low-voltage microgrid is developed using a non-cooperative game with incomplete information based on Bayesian game theory. In [Eksin et al., 2015], a Bayesian non-cooperative game is proposed to study energy consumption scheduling of energy users considering heterogeneous consumer preferences and uncertainty of renewable energy generation. A demand-side aggregation method for load scheduling of a large number of small-scale energy users is proposed in [Chapman and Verbič, 2015] using staggered clock-proxy auction method and game theory with incomplete information.

2.3.4 Consumer Behaviour and Demand-side Management

Modelling strategic decision-making of consumers has been identified as an important aspect in consumer-driven applications including sociology, economics, and energy markets [Shen and Su, 2007, Harrison and Rutstrom, 2009, Chrysopoulos et al., 2013]. The residential energy consumer behaviour modelling framework in [Chrysopoulos et al., 2013] decomposes the observed electrical load curves into customer activities and evaluates the impact of behavioural changes on the aggregated load curve. Methodical discrepancies between rational choice theory and alternative user behavioural models are explored in [Sanstad and Howarth, 1994]. In [Wilson and Dowlatabadi, 2007], different models of user decision-making from social sciences are compared and reviewed their applications in residential energy use.

In [Sakri et al., 2008], a method for an optimal bidding of distributed energy generators is studied by using a conjectural variation method while modelling the behaviour of all constituents in the power market. The article [Gillingham et al., 2009] reviews economic concepts underlying consumer behaviour in energy efficiency and conservation methods, and it provides an empirical evidence of market and consumer behavioural failures in energy efficiency literature to motivate policy intervention in energy markets. The factors that influence consumers' subscription behaviour in a demand-side management program are investigated in [Naeem et al., 2015]. The paper shows that customers' actual plans are significantly deviate from anticipated ideal plans. With the use of dynamic population models, [Ghorbaniparvar et al., 2015] investigates the effects of user decisions on a load shifting demand-side management approach.

Game theory is one of the popular mathematical tools to explore how people reason about their neighbours' actions to make their own decisions in a competitive environment. The standard dictate of game theory is to assume that users make rational choices to optimise their objectives. Demand-side management is one of the main applications where game theory has been widely used to study strategic behaviour of users conforming to the norm of rational behaviour.

The game-theoretic electric vehicle charging scheduling approach in [Bahrami and Parniani, 2014] develops a stochastic model to incorporate dynamics of starting times of electric vehicle charging of vehicle owners. The optimal electric vehicle charging schedules are determined assuming that users are rational in making decisions complying with the rationality axiom of conventional game theory. By taking consumer preferences on convenience over cost savings into account, [Bai et al., 2014] studies a game-theoretic approach for residential energy consumption scheduling assuming rational user behaviour. In [Sola and Vitetta, 2014], a non-cooperative game for distributed and autonomous demand-side management is studied with incomplete information available to users. The paper assumes that the users act rationally to determine their optimal energy consumption schedules that maximise expected utility defined as per conventional game theory. In [Eksin et al., 2015], a non-cooperative game-theoretic demand-side management is studied where users have heterogenous consumption preferences with incomplete information due to uncertain estimates of demand and renewable energy generation. The method regards users are rational in choosing energy consumption schedules based on classic game theory.

Evidence from many social experiments has demonstrated that people may not perform ideal, completely rational behaviour in real world when they face uncertainty and risk [Kahneman and Tversky, 1979]. Prospect theory has drawn great attention in various research communities as it can provide necessary tools to realise real world strategic decision-making of users under uncertainty and risk. In [Li and Mandayam, 2012], a prospect-theoretic approach is used to study subjective consumer behavioural impacts on a wireless random access game. In doing so, the Nash equilibria under both classic game-theoretic approach and prospect theory are compared. The prospect-theoretic approach in [Li and Mandayam, 2014] studies real-life decision-making in a wireless random access game and shows that deviations from classic game-theoretic assumptions can degrade the system throughput.

In [Jain and Deshpande, 2010], a cumulative prospect-theoretic approach is proposed to study the selection of energy generation units under risk to support future energy demand of a country based on an illustrative example. A broad discussion for exploring the potential of prospect theory to better understand how consumer decision making under risk and uncertainty can affect various smart grid application is given in [Saad et al., 2016]. In [Wang et al., 2014], interactions and energy exchange decisions between geographically-distributed consumer-owned energy storage devices are compared under both expected utility theory (classical game-theoretic approach) and prospect theory. In the system, a non-cooperative game is formulated among consumers who possibly own energy storage devices where they decide whether to charge or discharge storage devices. In parallel to the work [Wang et al., 2014], [Wang and Saad, 2015] investigates the effects from subjective consumer behaviour in the energy storage charging-discharging system using utility framing method derived from prospect theory. The method better understands the users' subjective evaluation of gains and losses with respect to a non-zero utility reference point. Interesting insights from prospect theory to study decision making in a consumer-centric demand side management method are investigated in [Wang et al., 2015b]. In particular, the paper investigates a load shifting approach for households and show that the load-shifting incurs significantly different outcomes when users do not to follow the conventional game-theoretic strategies due to their subjective behaviour.

2.4 Concluding Remarks

In this chapter, first we have summarised the basic terminology of non-cooperative game theory and prospect theory with essential definitions that will be used in the following chapters. Then we have provided an up-to-date survey of literature related to demand-side management in smart grid. Both decentralised and centralised methods have been proposed to optimally control distributed energy resources in demand-side management. Under decentralised control, non-cooperative game-theory has been widely used to investigate optimal demand-side management with self-interested energy users. In literature, modelling energy user behaviour has been identified as one of the key aspects of smart grid and the majority of demand-side management literature advocates game theory to model rational actions of energy users. However, research based on prospect theory has shown how real life user behaviour contravenes the conventional game-theoretic rationality assumption. Using insights from these works, we develop non-cooperative game-theoretic energy trading frameworks for small-scale demand-side management and then study impacts of non-ideal user behaviour on the energy trading systems in subsequent chapters of the thesis.

Chapter 3

Non-cooperative Game-theoretic Energy Trading for Demand-side Management in Smart Grid

In this chapter, a decentralised energy trading system between a CES device and residential energy users who own local PV energy generation capabilities is explored for demand-side management of a neighbourhood area network. The non-cooperative energy trading interactions of the participating users are investigated using a non-cooperative dynamic game. The chapter concludes with an extensive simulation analysis that illustrates the performance of the energy trading system in terms of energy cost savings for the participating users and peak-to-average ratio reductions for the main power grid.

3.1 Introduction

With the availability and rapid cost reductions of advanced battery technologies, energy storage devices located close to consumers are increasingly expected to facilitate effective demand-side management [Nourai et al., 2010]. CES devices are distributed on a neighbourhood-scale and connected to the low voltage side of distribution transformers in a neighbourhood area network that consists of a number of residential buildings [Ekanayake et al., 2012]. One of the primary advantages of CES devices is that they can effectively implement innovative small-scale energy management, such as in a gated residential community (e.g., a retirement village) [Zhu et al., 2012b]. Small-scale CES devices (several kW) can moderate household-distributed intermittent renewable power at the point of generation more efficiently than large central storage systems of hundreds of MW or substation-scale energy storage systems of several MW [Nourai et al., 2010]. Demand-side management approaches with CES devices can be used to efficiently utilise household-distributed renewable power sources to regulate demand-side load fluctuations without changing regular user energy demand profiles, as in some demand-side management methods [Mohsenian-Rad et al., 2010].

The energy trading management of the CES could be solved at a central microgrid controller, which would require accurate power information of individual network components for robust performance. However, obtaining accurate power information of residential consumers is difficult [Mohd et al., 2008], and controlling users' energy decisions from a central entity may be less realistic. These challenges require new perspectives to control CES devices that can meet users' individual satisfaction.

In this chapter, we introduce a novel energy trading system for load management of a grid-connected microgrid [Maity and Rao, 2010] that consists of a CES device, household-distributed PV panels, and energy consumers. In our framework, consumers who own PV panels can choose to sell their surplus PV energy to the grid and/or to charge the CES device, and can similarly buy energy from the CES device or grid when the electricity demand is high. Consumers in the microgrid individually determine their optimal energy trading bids for the next day considering local PV power generation and demand forecasts, and this leads to the day-ahead decentralised optimisation problem. This chapter has the following key contributions:

- We develop a non-cooperative dynamic repeated game between energy users to obtain Pareto-efficient unique Nash equilibrium strategies for optimal CES dispatching with minimal information exchange.
- We analyse the system performance and show that the proposed game provides significant load levelling for the grid and cost savings for the energy consumers in the neighbourhood area network. The system is benefited by an increasing fraction of participating users.

Game theory has been used in decentralised analytical models to find optimal dispatching strategies for controllable power generators, such as fuel cells and gas turbines, at the demand-side combined with consumer-owned energy storage devices to minimise the energy costs of users [Atzeni et al., 2013a]. Unlike the behind-the-meter storage scenarios as in [Atzeni et al., 2013a], to the best of our knowledge, this work is the first game-theoretic approach to find the optimal day-ahead schedule for a CES device at the distribution transformer. The main consideration of our analytical framework is to find users' energy trading strategies from uncontrollable and intermittent PV power generation at residences with minimal information exchange. The system is useful as it does not require users to invest in personal energy storage devices.

The chapter is structured as follows. Section 3.2 explains the system models that describe the configuration of the microgrid and energy costs. Section 3.3 develops the non-cooperative dynamic game among the participating users and explains its properties. Section 3.4 presents simulation results, which verify the performance of the energy trading system and Section 3.5 concludes the chapter.

3.2 System Model

We consider a grid-connected microgrid where residential electricity consumers are interconnected with a CES device to form a local electricity network. This section introduces the classification of the energy users, and the energy cost and pricing mechanisms used in the energy trading system.

3.2.1 The Configuration of the Microgrid

The fundamental building blocks of the microgrid considered in this paper include the power grid, residential energy users, and a CES unit as shown in Fig. 3.1. The demand-side of the community comprises two sets of users, non-participating users $\mathcal{N}$, and participating users $\mathcal{P}$. The users $\mathcal{N}$ are traditional energy consumers of the grid without any local power generation capability, and they do not participate to optimise our energy management framework. The users $\mathcal{P}$ may or may not have their own PV panels to generate energy, in addition to consuming energy from the conventional power grid, and they participate to optimise the energy management. Every participating user household is equipped with a controller that performs the decision making on their behalf, and households with PV panels do not have private energy storage facilities. Denote the set of all energy consumers

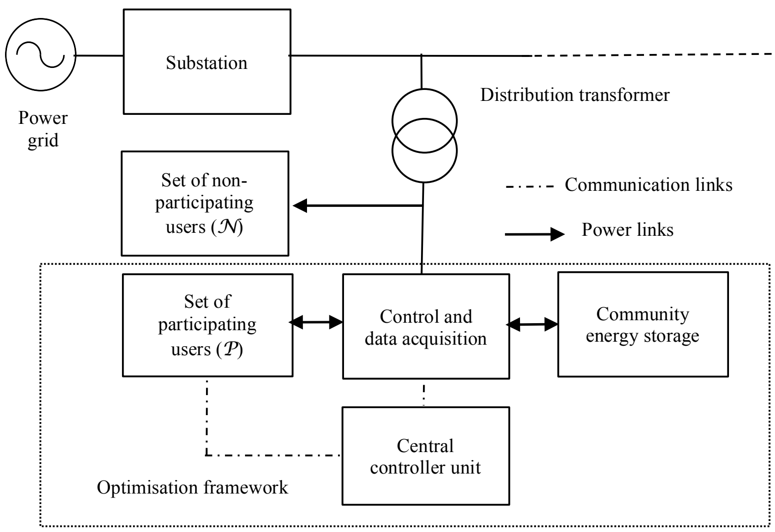

Fig. 3.1: The configuration of the microgrid with key entities.

within the community

$$Q = \mathcal{N} \cup \mathcal{P}. \tag{3.1}$$

We denote $\mathcal{T}$ as the entire time period of analysis, which is divided into M number of Δt equal time steps with control time $t = 1, 2, \cdots, M$. The participating users $\mathcal{P}$ can be partitioned into two distinct time-dependent categories: surplus users $\mathcal{S}(t)$ and deficit users $\mathcal{D}(t)$. Each surplus user $i \in \mathcal{S}(t)$ has energy production $g_i(t)$ from its own PV power generation that is greater than its electricity demand $e_i(t)$ at time t. Conversely, deficit users $j \in \mathcal{D}(t)$ are users with net energy deficits at time t: $g_j(t) < e_j(t)$. The latter set might also include users with no PV generation capabilities, but who still participate as users with energy deficits. Therefore

$$|\mathcal{P}| = I = I_{\mathcal{S}(t)} + I_{\mathcal{D}(t)}, \tag{3.2}$$

where $I_{\mathcal{S}(t)}$ is the number of users with surplus energy from their PV panels, and $I_{\mathcal{D}(t)}$ is the number of users with energy deficits at time t.

In our energy management framework, each user $n \in \mathcal{P}$ decides on their day-ahead strategy, considering their predicted energy demands and PV power generation across the period $\mathcal{T}$. The strategy determines the optimal energy amount that the user can sell to the CES device from its surplus PV energy, or the optimal energy amount that can be bought from the CES device to make up its deficit. This depends on the strategies of the other users $n' \in \mathcal{P} \backslash n$ and the aggregate load of the users $\mathcal{N}$. The energy balance for consumer $n \in \mathcal{P}$ at t is

$$l_n(t) = x_n(t) + e_n(t) - g_n(t), \tag{3.3}$$

where $l_n(t)$ is the energy consumption of the user $n \in \mathcal{P}$ from the grid at t, and $l_n(t) > 0$ if the user purchases energy from the grid: $l_n(t) < 0$ if the user sells energy to the power grid, and $x_n(t)$ is the energy amount that the user n trades with the CES device: positive if selling and negative if buying, which is the decision variable for the optimisation in this paper. The surplus PV energy for $n \in \mathcal{P}$ at t, $s_n(t)$, can be written as

$$s_n(t) = g_n(t) - e_n(t). \tag{3.4}$$

Without loss of generality, we assume that every user $n \in \mathcal{P}$ with a PV panel first consumes the generated energy according to its needs, and then, if there is any surplus/deficit, the amount of energy $x_n(t)$ that can be traded with the CES is determined. Finally, the energy balance in (3.3) determines the remaining amount of energy, $l_n(t)$, to sell to or purchase from the grid. For the users with surplus PV energy i.e., if $s_i(t) > 0$

$$0 \leq x_i(t) \leq s_i(t), \tag{3.5}$$

whereas for the users with energy deficits i.e., if $s_j(t) < 0$

$$s_j(t) \leq x_j(t) \leq 0. \tag{3.6}$$

Therefore, we can express the energy balance in (3.3) for consumer $n \in \mathcal{P}$ at time t as

$$l_n(t) = x_n(t) - s_n(t). \tag{3.7}$$

In the CES model, we assume that the maximum energy capacity and charging-discharging rates of the CES device are sufficient to support the participating users' optimal energy transactions. To consider conversion losses of the CES device, we introduce CES charging and discharging inefficiencies that are characterised by β^+ and β^-, respectively, where $0 \leq \beta^+ \leq 1$ and $\beta^- \geq 1$ [Atzeni et al., 2013a]. Explicitly, if x^+ amount of energy is sold to charge the CES device, only $\beta^+ x^+$ is charged, and to withdraw x^- amount of energy from the CES, $\beta^- x^-$ amount is discharged. Moreover, we include a leakage rate α for the CES device that results in reduction of stored energy with time ($0 \leq \alpha \leq 1$) [Atzeni et al., 2013a]. Therefore, if $q(t-1)$ represents the charge level at the beginning of time t, then the charge level at the end of t, $q(t)$, can be given as

$$q(t) = \alpha q(t-1) + \beta^+ \sum_{i \in \mathcal{S}(t)} x_i^+(t) - \beta^- \sum_{j \in \mathcal{D}(t)} x_j^-(t), \tag{3.8}$$

where $x_i^+(t)$, $x_j^-(t) \geq 0$ are charging and discharging transactions, respectively, and $(\beta^+ \sum_{i \in \mathcal{S}(t)} x_i^+(t) - \beta^- \sum_{j \in \mathcal{D}(t)} x_j^-(t))$ gives the net energy charging position of the CES device at t. Dynamic requirement parameters such as peak power capability and ramp rate limits of the CES device should be identified before the practical implementation of our system. Distribution losses of the network are neglected due to the short proximity between the elements of the residential microgrid of the neighbourhood area network [Caldognetto et al., 2014]. Assuming that the charge level of the CES at the beginning of the day, $\theta(0)$, is at its safe operational region, for continuous operation and to avoid over charging or discharging of the CES device during $\mathcal{T}$, we enforce a boundary condition [Abbey and Joos, 2009, Atzeni et al., 2013a]

$$q(M) = q(0). \tag{3.9}$$

3.2.2 Energy Cost Models

This section explains the pricing mechanisms for the energy consumers in the community. We use a grid energy cost model where the unit energy price at time t depends on the aggregate load on the grid at t, $L(t)$ [Atzeni et al., 2013a, Mohsenian-Rad et al., 2010]. $L(t)$ can be given as

$$L(t) = L_{\mathcal{N}}(t) + L_{\mathcal{P}}(t) \tag{3.10}$$

where $L_{\mathcal{N}}(t)$ and $L_{\mathcal{P}}(t)$ are the aggregate load on the grid by the non-participating and participating users, respectively, at time t. For non-negative pricing we require $L(t) > 0$. Assuming that at each time t, $L(t) < L_{\max}$, where $L_{\max}$ is the maximum load that the grid can support without causing an overload condition, the dynamic grid price function

$$p(t) = \phi_t L(t) \tag{3.11}$$

where ϕ_t is a positive time-of-use tariff constant, and is determined by the utility according to a day-ahead electricity market clearing process [Atzeni et al., 2013a]. The value of ϕ_t can vary from one time slot to another to impose a time-dependent pricing signal over $\mathcal{T}$, in addition to the real-time aggregate load dependency described above. Then the cost paid to the grid by any user $\tau \in Q$ at time t, $F_\tau(t)$, can be defined as

$$F_\tau(t) = p(t) l_\tau(t). \tag{3.12}$$

$F_\tau(t)$ is a quadratic and strictly convex function due to the grid price dependancy on aggregate load in (3.11). For a user $n \in \mathcal{P}$, $F_n(t)$ can be a positive or a negative value depending on whether they purchase energy from or sell energy to the grid. This pricing model considers the associated costs for any user can be different from one time slot to another, even if they exchange the same amount of energy with the grid.

The CES operator sets a time-dependent price $a(t)$ per unit energy at $t \in \mathcal{T}$, such that user $n \in \mathcal{P}$ receives (or pays)

$$P_n(t) = a(t) x_n(t). \tag{3.13}$$

The CES price $a(t)$ is set such that the equilibrium CES energy trading values $x_n(t)$ satisfy constraints (3.5) and (3.6) for all surplus and deficit users, respectively, at each $t \in \mathcal{T}$. Then, a linear combination of the upper and lower feasible price boundaries is selected to satisfy the continuity constraint (3.9).

Finally, the total cost imposed on the user $n \in \mathcal{P}$ at time t using (3.7), (3.12) and (3.13) is

$$C_n(t) = \phi_t L(t)(x_n(t) - s_n(t)) - a(t) x_n(t). \tag{3.14}$$

3.3 Dynamic Game

In this model, each user $n \in \mathcal{P}$ receives the energy prices set by the utility and by the CES operator, and then iteratively determines their optimal CES energy trading amount $x_n(t)$ at each time t to minimise their per-slot energy cost in (3.14). We assume that every user $n \in \mathcal{P}$ has an accurate prediction of their following day's energy requirements, and every user with a PV panel has a next day's PV power generation forecast.

We adopt a pure strategy dynamic non-cooperative game to analyse the multi-user scenario in this paper. The game is formulated as a finitely-repeated game, where the same players non-cooperatively play the same stage game $\mathcal{G}$ at times $t = 1, 2, \cdots, M$ [Brown and Shoham, 2008]. Here, we define the stage game $\mathcal{G}$ as played at any time $t \in \mathcal{T}$. The actions at each time t are determined by an iterative algorithm that proceeds until convergence to a stable solution for all users. If we define the strategy vector of participating users as $\boldsymbol{x} = [x_1(t), x_2(t), \cdots, x_I(t)]$, then the game $\mathcal{G}$ converges to the Nash equilibrium strategy profile

$$\boldsymbol{x}^* = [x_1^*(t), x_2^*(t), \cdots, x_I^*(t)]. \tag{3.15}$$

Nash equilibrium implies each user plays the best response to all other users who mutually play their Nash equilibrium strategies [Brown and Shoham, 2008]. Each stage game $\mathcal{G}$ can be described as follows.

1. *Players*: The set of participating users $\mathcal{P}$.
2. *Strategies*: Determining the CES energy transaction $x_n(t) \in \boldsymbol{X_n}$ for $n \in \mathcal{P}$ to maximize their payoff.
3. *Payoffs*: $U(x_n, \boldsymbol{x_{-n}}) \equiv U_n(t) = -C_n(t)$ for every $n \in \mathcal{P}$, where from (3.14),

$$U_n(t) = -\phi_t(l_n(t) + L_{-n}(t))(x_n(t) - s_n(t)) + a(t)x_n(t), \tag{3.16}$$

and $\boldsymbol{x_{-n}} = [x_1(t), x_2(t), \cdots, x_{n-1}(t), x_{n+1}(t), \cdots, x_I(t)]$ is the strategy profile of the users $\mathcal{P}$ except player n, and $L_{-n}(t)$ is the aggregate grid load of all community users except user n at time t. Also, $\boldsymbol{X}_n$ is the strategy set available to the player $n \in \mathcal{P}$ which subjects to the constraints (3.5) or (3.6), and (3.9).

Therefore, every user $n \in \mathcal{P}$ simultaneously solves the local optimisation problem to find

$$\tilde{x}_n(t) = \underset{x_n(t) \in \boldsymbol{X_n}}{\operatorname{argmax}} \; U(x_n, \boldsymbol{x_{-n}}), \tag{3.17}$$

until the game converges to the Nash equilibrium.

Proposition 1. *The solution of the game $\mathcal{G}$ between participating users converges to a unique Nash equilibrium.*

Proof. First, we can write (3.16) as a quadratic function with respect to $x_n(t)$

$$U_n(t) = \lambda_1 x_n(t)^2 + \lambda_2 x_n(t) + \lambda_3, \tag{3.18}$$

where $\lambda_1 = -\phi_t$, $\lambda_2 = (2\phi_t s_n(t) - \phi_t L_{-n}(t) + a(t))$ and $\lambda_3 = (L_{-n}(t) - s_n(t))\phi_t s_n(t)$. As $\lambda_1 < 0$, the second derivative of (3.18) with respect to $x_n(t)$ is negative and therefore (3.18) is strictly concave [Boyd and Vandenberghe, 2004]. Therefore each participating user's objective function in (3.17) is strictly concave and the continuous individual strategy sets are compact and convex due to linear inequalities, the existence of a unique Nash equilibrium solution of the game is guaranteed [Rosen, 1965]. □

Proposition 2. *The unique Nash equilibrium strategy profile $\boldsymbol{x}^*$ of the game $\mathcal{G}$ is Pareto optimal.*

Proof. A strategy profile is Pareto optimal when it is impossible to obtain another strategy profile that increases payoff of any one user without decreasing at least one other user's payoff [Brown and Shoham, 2008]. At $t \in \mathcal{T}$, given the price $a(t)$, the user $n \in \mathcal{P}$ determines its energy cost using (3.14). The game $\mathcal{G}$ results in Nash equilibrium between participating users (Proposition 1), and with the continuous and strictly convex energy cost model, any participating user requires concessions from at least one other participating user to improve their strategy by the second derivative test [Stephens et al., 2015]. Therefore, we can conclude that the Nash equilibrium strategy profile of $\mathcal{G}$ is Pareto optimal. □

An iterative algorithm was developed to evaluate the non-cooperative game between the users $\mathcal{P}$ at each time t. At each iteration r of the algorithm, user $n \in \mathcal{P}$ solves (3.17) using the aggregate load of all other users $n' \in \mathcal{P} \backslash n$ from the previous iteration $(r-1)$, $L_{-n}^{r-1}(t)$, knowing the ϕ_t and $a(t)$ values broadcast by the utility and the CES operator, respectively. This aggregate load signal is transmitted by the central controller of the system, which sums up the individual loads of each participating user. Note that disclosure of individual strategies amongst participating users is not required, which validates the use of a non-cooperative game.

3.4 Simulation Results

For the simulations in Sections 3.4.1, 3.4.2, 3.4.3, and 3.4.4 we assume 100% accurate predictions of PV energy and user energy demand profiles, and no conversion losses and leakage rate for the CES device i.e., $\beta^+ = 1$, $\beta^- = 1$, and $\alpha = 1$. Note that we will study the effects of forecasting errors and inefficiencies of the CES on the proposed system (PS) in Chapter 5.

To compare system performance, the following simulations consider a baseline without a CES device that incorporates a solar power feed-in system with net metering [SolarCity,], where residential PV energy producers sell excess power generated from their PV units directly to the grid. The baseline net-metering system (BNS) assumes that the users interact only with the grid, which uses the same energy cost model. We also assume that the utility adopts a one-for-one solar buyback scheme where it purchases solar energy at its retail selling price [Martin, 2012].

3.4.1 Preliminary Analysis of the Non-Cooperative Repeated Game

The primary impetus for a user to commit to the CES scheme is a reduction in electricity costs. If the cost savings of being a participating user outweigh the costs associated with becoming a participating user, then a non-participating member is motivated to invest in the CES scheme.

Fig. 3.2 shows the total community cost savings of our system compared to the baseline as a function of the fraction of the users $\mathcal{P}$, after the game is played within a single time slot. Here up to 40 deficit participating users were considered, whose surplus energies are uniformly distributed between $[-1.2, -0.8]$ kWh. The aggregate community load L is held constant at 40 kWh by varying $L_{\mathcal{N}}$. Only deficit users were considered here since the participating and non-participating members need to be indistinguishable with respect to their energy load, and (3.11) requires the total community load on the grid to be positive. The unit electricity price at the grid was fixed at 26.7 AU cents/kWh, which is equivalent to the residential peak unit energy price in [Ausgrid, 2014], while the CES's unit energy price increased with the fraction of participating users from 95% to 99% of the equilibrium grid price.

In Fig. 3.2, the cost savings initially increase as more users participate in our system and can offset their load from the more expensive grid to the CES device. However, as the fraction of users $\mathcal{P}$ increases the greater demand on the CES device leads to a greater CES unit energy price. As the energy price of the CES approaches the energy price of the grid, the potential cost savings are reduced and the total community cost savings saturate, and even decline; despite an increase in participating users. The total

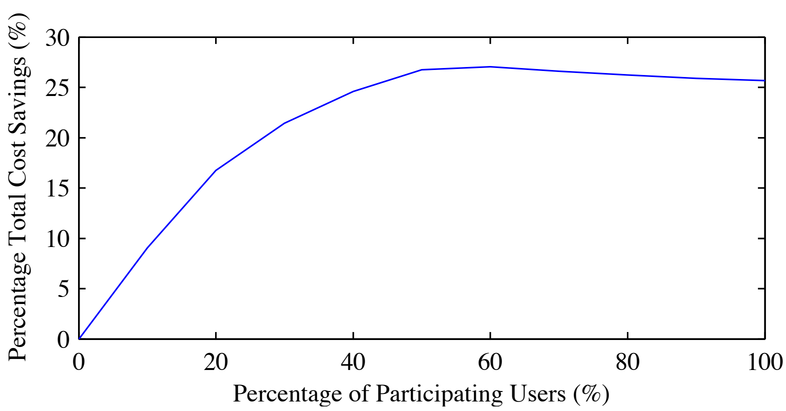

Fig. 3.2: Percentage total cost savings of the system played over one time slot with different fractions of participating users.

cost savings peak at a maximum of 27% with 60% participating users. On this basis, we select 30-50% participating users in the following simulations because of the diminishing returns of investing in the system (Fig. 3.2).

3.4.2 Performance of the Proposed System

We consider a community of 40 users where 40% of users (i.e., 16) actively participate in the proposed game. Data for the average daily domestic electricity demand profile and the average daily PV power generation profile of the community was obtained from [Jones et al., 2012], which uses metering data from the Western Power Network in Australia for a Spring day with average PV inverter capacity of 1.2 kW. We set $\Delta t = 30$ min and $T = 24$ h. Additionally, we assign one ϕ value for the duration of peak hours (16:00 – 23:00) and a different ϕ value for the remaining non-peak hours such that $\phi_{\text{peak}} = 1.5\ \phi_{\text{off peak}}$, as used in [Atzeni et al., 2013a], and we set the peak unit energy price of the grid to be 26.7 AU cents/kWh, as in [Ausgrid, 2014].

As anticipated, participating users charge the CES device during the daytime when the PV generation is high, and they partially draw energy from the CES device in peak energy consumption hours instead of solely relying on the main grid (see Fig. 3.3). This helps to flatten the aggregate load of the community on the power grid at peak hours (see Fig. 3.4).

At midday when there is peak solar irradiation, all participating users tend to have surplus energy from their PV panels. Fig. 3.5 shows that at such times the unit energy price paid by the utility to purchase this energy has considerably increased in our system compared to that of the baseline case. During peak-demand hours, participating users have energy deficits due to low or no PV power generation. However, participation in the game helps to decrease the unit energy price of the utility for the energy consumers by transferring energy demands to the CES device, which is also beneficial for the non-participating users

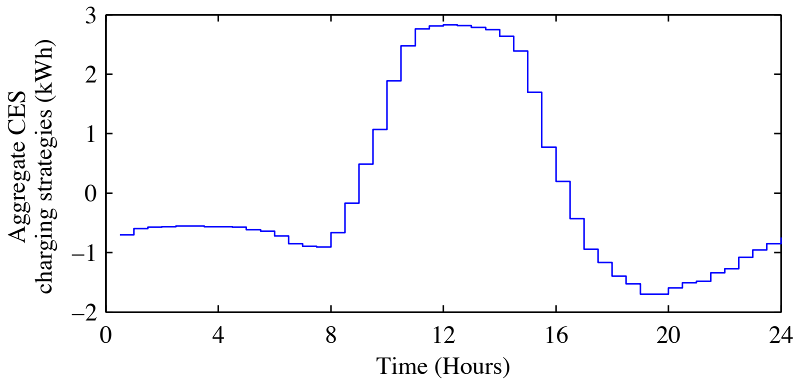

Fig. 3.3: Aggregate CES charging-discharging strategies from the game with 40% participating users.

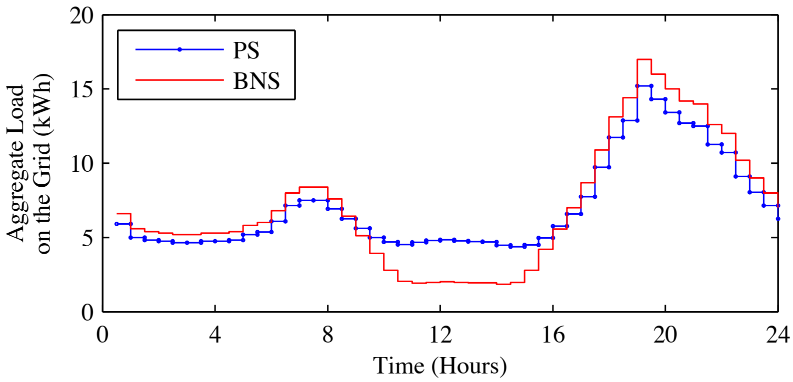

Fig. 3.4: Aggregate load on the grid with the PS and the BNS with 40% participating users.

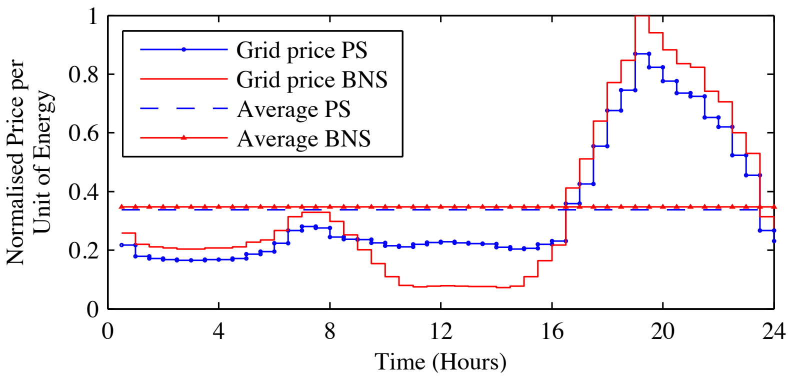

Fig. 3.5: Comparison between the normalised grid unit energy price of the PS and the BNS with 40% participating users.

$\mathcal{N}$. Our system can reduce the daily average energy costs of participating users by 26.0% compared to the baseline. Overall, the normalised average unit electricity price of the grid of the PS is 3.1% less than the baseline.

Generally, a lower peak-to-average ratio, with respect to demand, after energy management is preferable as it shows that the overall load on the grid is flattened [Mohsenian-Rad et al., 2010]. In our system, the peak-to-average ratio of the grid is 13.5% below that of the baseline. Finally, our system saves 10.5% of electricity costs for all energy users across the day, compared to the baseline.

3.4.3 Performance of the System with Different Fractions of Participating Users

This section investigates the behaviour of the day-ahead optimisation process for different percentages of participating users. We present results compared to the BNS for three different configurations: 30%, 40%, and 50% participating users, where each case has a total of 40 users, and the data for percentage average PV generation and energy demand profiles were generated for the three cases as described in Section 3.4.2. Table 3.1

Table 3.1: Performance metrics for different fractions of participating users.

Participating users	Participating user savings PS (%)	Average user savings PS (%)	CES revenue with PS (AU cents)	Average user savings FC (%)	PAR reduction PS (%)	PAR reduction FC (%)
30%	19.5	5.9	191	19.3	9.7	30.0
40%	26.0	10.5	275	27.9	13.5	40.0
50%	41.8	21.3	572	37.6	25.3	49.2

shows that the percentage average cost savings of the community in our system roughly double as the number of participating users increases by 10%. Also, the revenue gained by the CES operator, calculated by summing up $a(t) \sum_{n \in \mathcal{P}} x_n(t)$ at every time t, increases with the increasing fraction of participating users. Table 3.1 also shows that the PS can increase the reduction in peak-to-average ratio as the number of participating users increases.

3.4.4 Comparison of Cost Savings with the Fully Cooperative Case

Results from a centralised fully-cooperative (FC) case, where the participating users cooperate with each other and the CES operator for the three different configurations described in Section 3.4.3, are also presented in Table 3.1. Note that the results for the FC case are also calculated comparing with the baseline. In the FC case, we assume that community load and PV energy generation information of participating users for the entire time $\mathcal{T}$ is known perfectly by the CES operator, where it centrally minimises the total electricity cost paid by the community to the grid i.e., $\sum_{t=1}^{M} \phi_t L(t)^2$, using its storage capacity. In the FC model, all participating users act as a single entity and full knowledge of the percentage of the participation is required. Furthermore, the fully-cooperative model requires all participating users to follow CES dispatching strategies set by the CES operator that may not be optimal for the individual consumer, and it does not include a price signal for the CES energy transactions. Thus, it does not generate revenue for the CES operator. All of these reasons make the implementation of this fully-cooperative model very impractical.

Nevertheless, this socially optimal case is useful for comparison as an upper limit on performance. As the fraction of participating users increases, the performance of the PS becomes closer to that of the FC case. The PS can produce average user electricity cost savings that are nearly 50% of the FC setup in each configuration. Additionally, in most cases the participating user savings of the PS exceed the average user savings of the FC case.

3.5 Concluding Remarks

In this chapter, we have investigated a day-ahead decentralised energy management framework for a neighbourhood area network using a community energy storage (CES) device and consumer-owned photovoltaic (PV) energy. We have formulated an energy trading framework where residents who have surplus energy from their personal PV panels sell energy to the grid or to the CES device by selfishly minimising their individual energy costs. Participating residents with energy deficits can then purchase energy from the grid or CES device to minimise their costs. The decentralised decision making process of energy trading participating users was explored using a dynamic non-cooperative repeated game. An iterative algorithm was developed to perform the game in each control period, with minimal information exchange between participating users and which ultimately gives a Pareto-efficient pure strategy Nash equilibrium solution for the system. The simulation results show that the proposed system can regulate the overall electricity load on the grid across the day while reducing costs for energy consumers. Moreover, the energy cost savings and peak-to-average ratio reductions increase further as the fraction of participating users in the game increases. It is important to note that in this chapter, we have studied users' autonomy to minimise their energy costs. In the next chapter, we extend this work to investigate both CES operator's and users' autonomies to maximise own payoffs through energy trading.

Chapter 4

Hierarchical Energy Trading with a Community Energy Storage and Distributed Photovoltaic Energy Resources

In this chapter, we introduce a decentralised hierarchical energy trading system between a CES device and residential energy users with local PV energy generation facilities for competitive demand-side management of a neighbourhood area network. In particular, we extend the energy trading system in Chapter 3 to a bi-level energy trading system to investigate autonomies of both CES operator and users to maximise their individual payoffs. Then, we compare the bi-level energy trading system with two other potential energy trading systems with different CES operator models. Finally, simulations are carried out to demonstrate the performance of the bi-level energy trading system compared to the other two energy trading systems.

4.1 Introduction

Small-scale demand-side management with a CES device and behind-the-meter PV systems requires a feasible framework with suitable incentives for all players. One potential approach is to devise the load management optimisation that is controlled by a centralised entity. However, such centralised strategies may inflate costs for individual players. Moreover, robust operation of such a system would require system-wide information available to the controller including users' energy information that may increase the communication overhead [Weaver and Krein, 2009]. In addition, the residential users may not subscribe to such a demand-side management approach as the central entity controls their personal energy decisions. A decentralised framework that can distribute the energy decision-making to individuals would be an effective alternative to overcome the above challenges.

In this chapter, three energy trading systems with different CES operator structures are compared: a fully-competitive CES operator in a non-cooperative Stackelberg game, a benevolent CES operator that has socially favourable regulations with competitive consumers, and a centralised cooperative CES operator that collaborates with the users to minimise the total community energy costs. The former two systems use game-theoretic approaches where the CES operator (leader) moves first to maximise revenue. Users (followers) then follow the CES operator's actions to independently determine optimal CES energy trading strategies in a non-cooperative finitely repeated game. The fully-competitive CES operator has two degrees of freedom to maximise revenue in a non-cooperative Stackelberg game: energy price and their energy transactions with the grid. Conversely, the benevolent CES operator's ability to maximise revenue is restricted with only one degree of freedom, i.e., their energy transactions with the grid, in a Stackelberg game. The centralised system serves as a baseline to compare the performance of the decentralised game-theoretic energy trading systems. We have the following main contributions in this work:

1. The non-cooperative Stackelberg game between the fully-competitive CES operator and users has a unique Stackelberg equilibrium where users obtain unique Pareto-optimal Nash equilibrium CES energy trading strategies.

2. Performance analysis demonstrates,

   - Unlike in the centralised cooperative system, both CES operator and users are simultaneously benefited in the fully-competitive system while the grid experiences load levelling.

   - The community economic benefit is greater with the fully-competitive system than the benevolent CES model, and the fully-competitive system can be implemented effectively with least CES battery storage capacity of the three models.

The majority of Stackelberg game-theoretic demand-side management methods in literature exploit demand flexibility of consumers to obtain optimal system-wide objectives [Kilkki et al., 2015, Yu and Hong, 2016a, Chen et al., 2011b]. For example, the Stackelberg game in [Yu and Hong, 2016a] achieves the optimal load control of electrical appliances through an effective real time pricing method. To the best of our knowledge, few game-theoretic works achieve optimal load management by utilising energy from distributed energy resources as an alternative to reshaping consumer demand profiles [Atzeni et al., 2013b, Atzeni et al., 2013a]. For example, the non-cooperative game in [Atzeni et al., 2013a] determines optimal power settings of consumer-owned controllable power sources, such as gas turbines and energy storage devices, to minimise energy costs. In contrast to the use of consumer-owned energy storage devices as in [Atzeni et al., 2013a], we study the use of increased flexibility of a centralised CES device to utilise uncontrollable and intermittent PV power generation to achieve demand-side management without reshaping user demand. To this end, we investigate the leader-follower interaction between the CES operator and the users using Stackelberg games.

This chapter has two key differences to the work in Chapter 3 where a non-cooperative dynamic game between users is studied evaluating only users' autonomy to minimise costs. First, here, we devise bi-level energy trading systems to incorporate autonomies of both CES operator and users to minimise energy costs using Stackelberg games. We also investigate the trade-off between the CES capacity and community benefits, whereas Chapter 3 does not impose energy capacity constraints for the CES device by assuming that it has sufficient capacity at all times.

The remainder of this chapter is structured as follows. The system models are described in Section 4.2, and Section 4.3 describes the centralised energy trading system. The two game-theoretic energy trading systems are discussed in Section 4.4. Section 4.5 discusses simulation results, and conclusions are drawn in Section 4.6.

4.2 System Configuration

In this section, we describe the classification of energy consumers and the models of energy costs and the CES device.

4.2.1 Demand-Side Model

The demand-side of the community is divided into participating users $\mathcal{P}$ and non-participating users $\mathcal{N}$. The users $\mathcal{P}$ have their own PV panels without local energy storage devices, and they participate in the energy management optimisation by trading energy with the grid and/or the CES device. We assume that each user in $\mathcal{P}$ has a decision-making controller in their household to perform their local energy trading optimisation. The users $\mathcal{N}$ consume energy only from the grid as they do not have local power generation capabilities and do not participate in the demand-side management optimisation.

The users $\mathcal{P}$ are subdivided into two time-dependent categories: surplus users $\mathcal{S}(t)$ and deficit users $\mathcal{D}(t)$. We divide the time period $\mathcal{T}$, typically one day, into M equal time steps of length Δt with discrete time $t = 1, 2, \cdots, M$. We consider $|\mathcal{S}(t)| = I_{\mathcal{S}(t)}$, $|\mathcal{D}(t)| = I_{\mathcal{D}(t)}$, and $|\mathcal{P}| = I = I_{\mathcal{S}(t)} + I_{\mathcal{D}(t)}$.

At each time t, user $i \in \mathcal{S}(t)$ evaluates the optimal energy amount that they can sell to the CES device, and user $j \in \mathcal{D}(t)$ decides optimal energy amount that can be bought from the CES device. These strategies are determined day-ahead, and we assume that the users $\mathcal{P}$ have accurate forecasts of their energy demands and PV power generation for the next day. According to the energy balance at user $n \in \mathcal{P}$

$$l_n(t) = x_n(t) + e_n(t) - g_n(t). \tag{4.1}$$

Note that $x_n(t) > 0$ when the user is charging (or selling energy to) the CES device and $x_n(t) < 0$ when discharging (or buying energy from) the CES device. The surplus energy of $n \in \mathcal{P}$ at time t is given by $s_n(t) = g_n(t) - e_n(t)$. We specify

$$\begin{aligned} 0 \leq x_i(t) \leq s_i(t), \quad \forall i \in \mathcal{S}(t),\ t \in \mathcal{T}, \\ s_j(t) \leq x_j(t) \leq 0, \quad \forall j \in \mathcal{D}(t),\ t \in \mathcal{T}. \end{aligned} \tag{4.2}$$

4.2.2 Community Energy Storage Model

In this chapter, the energy storage model is similar to that in [Atzeni et al., 2013a]. At each time t, the CES device may exchange energy $l_Q(t)$ with the grid in addition to its energy transactions with the users $\mathcal{P}$. Here, $l_Q(t) > 0$ if the CES device is charging from the grid, and $l_Q(t) < 0$ if it is selling energy to the grid.

Without loss of generality, consider splitting $x_n(t)$ and $l_Q(t)$ such that $x_n(t) = x_n^+(t) - x_n^-(t)$ and $l_Q(t) = l_Q^+(t) - l_Q^-(t)$ where $x_n^+(t),\ l_Q^+(t) \geq 0$ are the charging strategy profiles and $x_n^-(t),\ l_Q^-(t) \geq 0$ are the discharging strategy profiles of the CES device at time t. Once inefficiencies are introduced, all optimal solutions satisfy $x_n^+(t)x_n^-(t) = 0$ and $l_Q^+(t)l_Q^-(t) = 0$ at all times to avoid simultaneous charging and discharging of the CES device [Atzeni et al., 2013a]. We introduce CES leakage rates β^+ and β^- to consider conversion losses of the CES device. For instance, if x^+ energy is sold to the CES device, then the charge level only increases by $\beta^+ x^+$. Similarly, $\beta^- x^-$ energy must be discharged to obtain x^- energy from the CES device. If $q(t-1)$ is the charge level at the beginning of time t, then $q(t)$ is given by

$$q(t) = \alpha q(t-1) + \beta^+ \chi^+ - \beta^- \chi^- \tag{4.3}$$

where $\chi^+ = \left[\sum_{n=1}^{I} x_n^+(t) + l_Q^+(t)\right]$ and $\chi^- = \left[\sum_{n=1}^{I} x_n^-(t) + l_Q^-(t)\right]$.

Using (4.3), we write (4.4) to ensure the CES charge level within its energy capacity limit at each time t as

$$\mathbf{0} \prec q(0)\boldsymbol{\eta} + \Psi\left(\boldsymbol{\chi}^+ - \boldsymbol{\chi}^-\right)\boldsymbol{\beta} \preceq \boldsymbol{Q_M} \tag{4.4}$$

where $q(0)$ is the initial charge level, and $\boldsymbol{Q_M} \in \Re^{M\times 1}$ with all its entries being Q_M. Additionally, $\boldsymbol{\eta} \in \Re^{M\times 1}$ has $[\eta]_v = \alpha^v$, $\Psi \in \Re^{M\times M}$ is a lower triangular matrix that has elements $[\Psi]_{v,w} = \alpha^{v-w}$, $\boldsymbol{\beta} = [\beta^+, \beta^-]^T$, $\mathbf{0}$ is the M-dimensional zero column vector, and $\boldsymbol{\chi}^+$, $\boldsymbol{\chi}^-$ are the M-dimensional column vectors with all their entries being χ^+, χ^-, respectively.

Assuming $q(0)$ is within the CES device's safe operating region, we set (6.6) to ensure the continuous operation of the CES device for the next day and to prevent over-charging or over-discharging during $\mathcal{T}$ [Chen et al., 2012]

$$q(M) = q(0). \tag{4.5}$$

4.2.3 Energy Cost Models

The unit electricity price of the grid at time t is assumed to have a constant baseline component and a variable real-time component that is proportional to the total grid load at time t [Mohsenian-Rad et al., 2010, Atzeni et al., 2013a]. In this work, the total grid load at time t is $L(t) = \sum_{n=1}^{I} l_n(t) + l_Q(t) + L_{\mathcal{N}}(t)$. In this paper, we assume, at each time t, $0 < L(t)$ for non-negative grid pricing and $L(t) < L_{\max}$ where $L_{\max}$ is the maximum allowable load on the grid without compromising voltage and line capacity limits of the grid. The unit electricity price of the grid at time t is given by $p(t) = \delta_t + \phi_t L(t)$ where δ_t and ϕ_t are determined according to a day-ahead market clearing process [Atzeni et al., 2013a]. With similar analysis to [Mohsenian-Rad et al., 2010], the resulting grid energy cost function at time t, $p(t)L(t)$, is a strictly convex function with respect to $L(t)$.

In our game-theoretic systems, the CES operator adopts prices for energy transactions with the users $\mathcal{P}$. Then, in these systems $C_n(t)$ is given by

$$C_n(t) = p(t)l_n(t) - a(t)x_n(t) \tag{4.6}$$

where $l_n(t)$ is given by (4.1). Both fully-competitive and benevolent CES operators obtain revenue through energy trading with the grid and the users $\mathcal{P}$. Assuming that the CES operator exchanges energy with the grid at the grid energy price, we consider the CES revenue as

$$R = \sum_{t=1}^{M} \quad -a(t)\sum_{n=1}^{I} x_n(t) - p(t)l_Q(t) \Bigg). \tag{4.7}$$

However, in the centralised energy trading system, the CES operator does not obtain revenue from energy trading with the users $\mathcal{P}$. In this regard, we do not consider a separate revenue function as (4.7), and the cost of user $n \in \mathcal{P}$ is derived as in (4.6) disregarding the term $a(t)x_n(t)$.

4.3 Centralised Energy Trading System

This section describes the community energy trading system with a centralised cooperative CES operator that solves the optimisation problem of minimising the total energy cost paid by the entire community to the grid. Note that this centralised approach serves as a baseline to compare the performances of the decentralised game-theoretic systems in Section 4.4. Here, we assume that the users $\mathcal{P}$ communicate their energy demand and PV energy generation profiles to the CES operator, and the operator also has the perfect knowledge of the community participation percentage. The CES operator schedules the energy transactions across the community by solving the optimisation problem

$$\min \sum_{t=1}^{M} p(t)L(t) \tag{4.8}$$

subjects to constraints (4.2), (4.4), and (4.5).

Note that in this system, (4.8) does not include a price signal for the CES operator's energy transactions with the users $\mathcal{P}$ and consequently, the operator has no direct incentive. It also requires impractical information exchange and cooperation. The cooperating participating users similarly do not have direct incentives as their personal energy costs may inflate for the benefit of the overall community. All of these reasons make the practical implementation of the centralised cooperative energy trading system less feasible. Even though this centralised approach is not appropriate for the general circumstances of the considered energy trading scenario, it is still a potential implementation of the energy trading between the CES device and the users $\mathcal{A}$.

4.4 Decentralised Energy Trading Systems

In our decentralised energy trading systems, the CES operator, as the leader, interacts with the users $\mathcal{P}$ to maximise their revenue (4.7). The users $\mathcal{P}$ follow the leader's actions to minimise their individual energy costs in (4.6) by manipulating $x_n(t)$. We develop Stackelberg game-theoretic frameworks to analyse the hierarchical CES-user energy trading interactions. To derive the solutions to the Stackelberg games, we adopt insights from backward induction [Brown and Shoham, 2008]. To this end, first, the actions of the users $\mathcal{P}$ are derived based on the knowledge of actions of the CES operator. Then our analysis proceeds backward to reason the actions of the CES operator.

4.4.1 Objective of the Participating Users

Here, each user $n \in \mathcal{P}$ seeks to minimise their personal energy costs. Therefore, in response to any suitable $\boldsymbol{\rho} = [\boldsymbol{a},\ \boldsymbol{l_Q}]$ of the CES operator, user $n \in \mathcal{P}$ minimises their energy cost in (4.6) at each time t. The cost function (4.6) is quadratic with respect to both $l_n(t)$ and $x_n(t)$. We consider

$$C_n(t) = K_2 l_n(t)^2 + K_1 l_n(t) + K_0 \tag{4.9}$$

where $K_2 = \phi_t$, $K_1 = (\phi_t L_{-n}(t) + \delta_t - a(t))$, and $K_0 = -a(t)s_n(t)$.

Since (4.9) depends on the actions of the other users $n' \in \mathcal{P}\backslash n$, we formulate a non-cooperative game $\Gamma \equiv \langle \mathcal{P}, \mathcal{X}, \mathcal{C} \rangle$ among the users $\mathcal{P}$ at each time $t \in \mathcal{T}$ to determine their optimal strategies. Here, $\mathcal{X} = \prod_{n=1}^{I} \boldsymbol{X_n(t)}$ where $\boldsymbol{X_n(t)}$ of user $n \in \mathcal{P}$ subject to constraints (4.2), and $\mathcal{C} = (C_1(t), \ldots, C_I(t))$. We denote $\boldsymbol{x(t)} = [x_1(t), \cdots, x_I(t)]$. Each user $n \in \mathcal{P}$ selects their strategy $x_n(t) \in \boldsymbol{X_n(t)}$ to minimise the cost function $C_n(x_n(t), \boldsymbol{x_{-n}(t)}) \equiv C_n(t)$. Here, $\boldsymbol{x_{-n}(t)}$ is the CES energy transaction strategy profile of the users $n' \in \mathcal{P}\backslash n$. Therefore, each user $n \in \mathcal{P}$ determines

$$\tilde{x}_n(t) = \underset{x_n(t) \in \boldsymbol{X_n(t)}}{\operatorname{argmin}} \; C_n(x_n(t), \boldsymbol{x_{-n}(t)}). \tag{4.10}$$

To make the game-theoretic analysis tractable, we assume that the users $\mathcal{P}$ have accurate day-ahead predictions of PV power generation and energy demand. Consequently, playing the game Γ at each time $t = 1, 2, \cdots, M$ by the users $\mathcal{P}$ using $\boldsymbol{\rho}$ turns into a non-cooperative finitely repeated game with perfect information where Γ is the stage game [Brown and Shoham, 2008].

Proposition 3. *For any given values of $a(t)$ and $l_Q(t)$, the stage game Γ obtains a unique pure-strategy Nash equilibrium.*

Proof. Nash equilibrium implies no player can gain by unilaterally changing their own strategy while the others play their Nash equilibrium strategies [Brown and Shoham, 2008]. For feasible $\boldsymbol{x_{-n}(t)}$, (4.9) is strictly convex since its second derivative with respect to $x_n(t)$ is positive as $\phi_t > 0$ [Boyd and Vandenberghe, 2004]. Therefore, each participating user's objective function in (4.10) is strictly convex. Additionally, the individual strategy sets are compact and convex due to linear inequalities (4.2). Therefore, a unique Nash equilibrium with pure strategies for the game Γ is obtained [Rosen, 1965]. □

The best response $\tilde{x}_n(t)$ of user $n \in \mathcal{P}$ to $\boldsymbol{x_{-n}(t)}$ can be found using

$$\left.\frac{\partial C_n(t)}{\partial x_n(t)}\right|_{x_n(t)=\tilde{x}_n(t)} = 2K_2(\tilde{x}_n(t) - s_n(t)) + K_1 = 0. \tag{4.11}$$

By solving (4.11) for all participating users I, using the expressions of K_1 and K_2 in (4.9), the optimal response of user $n \in \mathcal{P}$ at the Nash equilibrium, $\tilde{x}^*_n(t)$, can be written as a function of the CES operator's output variables $a(t)$ and $l_Q(t)$

$$\begin{aligned} \tilde{x}^*_n(t) &= s_n(t) - \varepsilon(t), \\ \varepsilon(t) &= -(I+1)^{-1}[\phi_t^{-1}(a(t) - \delta_t) - l_{\mathcal{P}}(t) - l_Q(t)]. \end{aligned} \tag{4.12}$$

Given the Nash equilibrium as in (4.12), parameters δ_t and ϕ_t can be chosen such that $\tilde{x}_n^*(t)$ satisfies (4.2) for given $a(t)$, $l_Q(t)$, and $L_{\mathcal{N}}(t)$. However, for general application of our system, we consider constraints in the CES operator's revenue maximisation problem so that the CES operator's selection of $a(t)$ and $l_Q(t)$ assures the Nash equilibrium (4.12) satisfies (4.2). This procedure is explained in the next subsection.

4.4.2 Objective of the Community Energy Storage Operator

In the decentralised energy trading setting, the CES operator's primary objective is to maximise the revenue in (4.7). According to backward induction, if we substitute (4.12) into (4.7), the CES operator's utility maximisation can be simplified to a quadratic optimisation problem to determine

$$\boldsymbol{\rho}^* = \underset{\boldsymbol{\rho}\in\mathcal{Q}}{\operatorname{argmax}} \sum_{t=1}^{M} (\lambda a(t)^2 + \mu a(t) + \nu l_Q(t)^2 + \xi l_Q(t)) \tag{4.13}$$

where $\lambda = -I(I+1)^{-1}\phi_t^{-1}$, $\mu = I(I+1)^{-1}(L_{\mathcal{N}}(t)+\phi_t^{-1}\delta_t) - \sum_{n=1}^{I} s_n(t)$, $\nu = -\phi_t(I+1)^{-1}$, and $\xi = -(I+1)^{-1}(\phi_t L_{\mathcal{N}}(t) + \delta_t)$. When the users' actions in (4.12) satisfy (4.2), at each time t, the CES operator selects $a(t)$ and $l_Q(t)$ such that

$$\left.\begin{aligned} &\max[\{s_j(t)\}_I] \le \varepsilon(t) \le 0, && \text{if } \mathcal{P} = \mathcal{D}(t),\\ &0 \le \varepsilon(t) \le \min[\{s_i(t)\}_I], && \text{if } \mathcal{P} = \mathcal{S}(t),\\ &\varepsilon(t) = 0, && \text{otherwise.} \end{aligned}\right\} \tag{4.14}$$

Hence, in addition to (4.4) and (4.5), we consider (4.14) in $\mathcal{Q}$ depending on the nature of the users $\mathcal{P}$ at time t.

The objective function in (4.13) is strictly concave since its Hessian matrix is negative definite for all $\boldsymbol{a}, \boldsymbol{l_Q} \in \mathcal{Q}$ as coefficients $\lambda, \nu < 0$. Moreover, $\mathcal{Q}$ is non empty, closed and convex as it is only subject to linear constraints. Therefore, (4.13) always has a unique maximum [Boyd and Vandenberghe, 2004].

4.4.3 Benevolent CES Operator Model

After describing the objectives of the users $\mathcal{P}$ and the CES operator, in this section, we analyse the Stackelberg energy trading competition between the benevolent CES operator and the users $\mathcal{P}$. Consider if $x_n(t) = s_n(t)$, $\forall n \in \mathcal{P}$ and $\forall t \in \mathcal{T}$, then these user strategies are at the Nash equilibrium of the game Γ if and only if $\varepsilon(t) = 0$ at each time t. As a result

$$a(t) = \delta_t + \phi_t(l_Q(t) + L_{\mathcal{N}}(t)). \tag{4.15}$$

In this model, the price constraint (4.15) applies as an auxiliary constraint for the CES operator at each time t when maximising their revenue in addition to (4.4) and (4.5). Then, the objective function in (4.13) can be written as a function of $l_Q(t)$ only by substituting (4.15) into (4.13). Thus, the objective of the CES operator in the benevolent scenario is

$$\bar{\boldsymbol{l}}_{\boldsymbol{Q}} = \operatorname*{argmax}_{\boldsymbol{l}_{\boldsymbol{Q}} \in \mathcal{Q}} \sum_{t=1}^{M} (\gamma_1 l_Q(t)^2 + \gamma_2 l_Q(t) + \gamma_3) \tag{4.16}$$

where $\gamma_1 = -\phi_t$, $\gamma_2 = -\delta_t - \phi_t(L_{\mathcal{N}}(t) + \sum_{n=1}^{I} s_n(t))$, and $\gamma_3 = -\sum_{n=1}^{I} s_n(t)(\delta_t + \phi_t L_{\mathcal{N}}(t))$.

In the Stackelberg game, the CES operator, as the leader, firstly determines optimal $l_Q(t)$ by solving (4.16) and then their energy price $a(t)$ using (4.15) for each time $t \in \mathcal{T}$. Using these values, the users $\mathcal{P}$ determine optimal strategies of $x_n(t)$ by playing the game Γ at each time t. As a result, at the Nash equilibrium of the game Γ, the energy requirements of the users $\mathcal{P}$ are shifted on to the CES device such that $\tilde{x}_n^*(t) = s_n(t)$. Hence, $\tilde{l}_n^*(t) = (\tilde{x}_n^*(t) - s_n(t)) = 0$, $\forall n \in \mathcal{P}$, $\forall t \in \mathcal{T}$.

In this system, the CES operator does not have full freedom to maximise the revenue in (4.13) with the additional constraint (4.15). Here, $\bar{p}(t) = \delta_t + \phi_t(L_{\mathcal{N}}(t) + \bar{l}_Q(t)) = \bar{a}(t)$ where $\bar{l}_Q(t)$ is the CES device's grid load at its maximum revenue in (4.16) since the users $\mathcal{N}$ and the CES device are the only remaining energy loads on the grid as the users $\mathcal{P}$ shift their net energy requirements $s_n(t)$ to the CES device. We consider this as a benevolent CES operator that is regulated by the users $\mathcal{P}$ to amalgamate all their energy requirements into one entity with storage capabilities for better demand-side management.

4.4.4 Fully-competitive CES Operator Model

This section explains the non-cooperative Stackelberg game between the fully-competitive CES operator and the users $\mathcal{P}$. In the system, the CES operator first sets $\boldsymbol{\rho}$ to maximise their revenue in (4.13) and broadcasts them to the users $\mathcal{P}$. Using these signals, the users $\mathcal{P}$ repeat the non-cooperative game Γ at each time t. In contrast to the benevolent CES model, this system adopts relaxed constraints (4.14) for the selection of $a(t)$ and $l_Q(t)$ of the CES operator. Hence, the CES operator's objective is identical to (4.13).

In this scenario, the bi-level interaction between the CES operator and the users $\mathcal{P}$ can be formulated as a non-cooperative Stackelberg game Υ. We represent the strategic form of Υ as $\Upsilon \equiv \langle \{\mathcal{L}, \mathcal{P}\}, \{\mathcal{Q}, \mathcal{X}\}, \{R, \mathcal{C}\} \rangle$ where the CES operator $\mathcal{L}$ is the leader, the users $\mathcal{P}$ are the followers, and all other notations are defined as in the preceding sections.

Proposition 4. *The game Υ obtains a unique Stackelberg equilibrium.*

Proof. The non-cooperative game Γ between the users $\mathcal{P}$ has a unique Nash equilibrium for given $a(t)$ and $l_Q(t)$ of the CES operator (see Proposition 1). There is also a unique solution of the CES operator's revenue maximisation (4.13). Therefore, the game Υ obtains a unique Stackelberg equilibrium as soon as the CES operator determines their unique revenue maximising strategy $\boldsymbol{\rho^*}$ while the users $\mathcal{P}$ play their unique Nash equilibrium strategy profile $\boldsymbol{x^*(t)}$ at each time t. $\square$

Note that, according to backward induction, the Stackelberg equilibrium strategies of the CES operator and the users $\mathcal{A}$, $\boldsymbol{\rho^*}$ and $x_n^*(t) \in \boldsymbol{x^*(t)}$, are equal to the solution of (4.13) and the resulting $\tilde{x}_n^*(t)$ after substituting $a^*(t)$, $l_Q^*(t) \in \boldsymbol{\rho^*}$ in (4.12), respectively. The Stackelberg equilibrium strategies of the CES operator and the users $\mathcal{P}$, $\boldsymbol{\rho^*}$ and $\boldsymbol{x^*(t)}$, respectively, satisfy

$$C_n(\boldsymbol{x^*(t)},\ \boldsymbol{\rho^*}) \leq C_n(x_n(t), \boldsymbol{x^*_{-n}(t)}, \boldsymbol{\rho^*}),$$
$$\forall n \in \mathcal{P},\ \forall x_n(t) \in \boldsymbol{X_n(t)},\ \forall t \in \mathcal{T}, \tag{4.17}$$

$$R(\boldsymbol{X^*}, \boldsymbol{\rho^*}) \geq R(\boldsymbol{X^*}, \boldsymbol{\rho}),\ \forall \boldsymbol{\rho} \in \mathcal{Q} \tag{4.18}$$

where $\boldsymbol{x^*_{-n}(t)}$ is the Nash equilibrium strategy profile of the users $\mathcal{P}$ except user n at time t, and $\boldsymbol{X^*} = (\boldsymbol{x^*(1)}^T, \ldots, \boldsymbol{x^*(M)}^T)$ is the M-tuple of Nash equilibrium strategy profiles of the users $\mathcal{P}$ at each t in response to $\boldsymbol{\rho^*}$.

Proposition 5. *At the Stackelberg equilibrium of the game Υ, the Nash equilibrium CES energy trading strategies of the users $\mathcal{P}$ achieved by playing the game Γ are Pareto optimal.*

Proof. Let us consider the energy trading strategies of the users $\mathcal{P}$ and the CES operator at the Stackelberg equilibrium of the game Υ at any $t \in \mathcal{T}$: $[\boldsymbol{x^*(t)}, a^*(t), l_Q^*(t)]$. Assume there is any feasible $\boldsymbol{x^{'}(t)} (\neq \boldsymbol{x^*(t)})$ such that $\boldsymbol{x^{'}(t)}$ Pareto dominates $\boldsymbol{x^*(t)}$. Define the aggregate CES energy trading amount of the users $\mathcal{P}$ at time t, $X_{\mathcal{P}}(t)$, at $\boldsymbol{x^{'}(t)}$ and $\boldsymbol{x^*(t)}$ as $X_{\mathcal{P}}^{'}(t)$ and $X_{\mathcal{P}}^*(t)$, respectively, where $X_{\mathcal{P}}^{'}(t) = X_{\mathcal{P}}^*(t) + \theta X_{\mathcal{P}}^*(t)$. First, assume θ is a non-zero scalar. Due to the introduced change of $X_{\mathcal{P}}^*(t)$ to $X_{\mathcal{P}}^{'}(t)$, the CES device is forced to over-charge or over-discharge violating (4.5). Therefore, the CES operator has to divert from their strategy $l_Q^*(t)$ to $l_Q^{'}(t) = l_Q^*(t) - \theta X_{\mathcal{P}}^*(t)$ in order to satisfy (4.5) that ensures the sustainable operation of the CES device throughout the day. For example, if the CES charge level rises due to the introduced change, the CES operator has to discharge the increased amount of energy to the grid. Note that, in doing so, the Stackelberg equilibrium grid price $p^*(t)$ does not change as the total grid load does not change.

Then at the new operating point $C_{CES}(t)$ is given by

$$C_{CES}(t) = a^*(t)X_{\mathcal{P}}^{'}(t) + p^*(t)l_Q^{'}(t), \tag{4.19}$$

and $C_{\mathcal{P}}(t)$ is

$$C_{\mathcal{P}}(t) = p^*(t)\left(X_{\mathcal{P}}^{'}(t) - S_{\mathcal{P}}(t)\right) - a^*(t)X_{\mathcal{P}}^{'}(t) \tag{4.20}$$

where $S_{\mathcal{P}}(t) = \sum_{n=1}^{I} s_n(t)$. By substituting $X'_{\mathcal{P}}(t) = X^*_{\mathcal{P}}(t) + \theta X^*_{\mathcal{P}}(t)$ and $l'_Q(t) = l^*_Q(t) - \theta X^*_{\mathcal{P}}(t)$ into (4.19) and (4.20), it is evident that if $C_{\mathcal{P}}(t)$ decreases, then $C_{CES}(t)$ increases and vice versa. Such a situation is not led by the CES operator and hence there is no feasible $\boldsymbol{x}'(\boldsymbol{t}) \in \mathcal{X} \backslash \boldsymbol{x}^*(\boldsymbol{t})$ that Pareto dominates $\boldsymbol{x}^*(\boldsymbol{t})$ after obtaining the Stackelberg equilibrium.

Moreover, when $\theta = 0$, $X'_{\mathcal{P}}(t) = X^*_{\mathcal{P}}(t)$. This implies that if at least one user in $\mathcal{P}$ changes their Nash equilibrium strategy to another strategy, then the other users have to change their aggregate CES energy trading strategies by the same energy amount such that $X'_{\mathcal{P}}(t) = X^*_{\mathcal{P}}(t)$. In this situation, the grid price $p^*(t)$ and the unit energy price of the CES device $a^*(t)$ are unchanged. Hence, a reduction in one user's energy cost due to a change in their operating point would lead to an increase in the cost of at least one of the other users. Hence, with $\theta = 0$, for given $[a^*(t), l^*_Q(t)]$, it is infeasible to adopt any $\boldsymbol{x}'(\boldsymbol{t}) \in \mathcal{X} \backslash \boldsymbol{x}^*(\boldsymbol{t})$ such that $C_n(\boldsymbol{x}'(\boldsymbol{t})) \leq C_n(\boldsymbol{x}^*(\boldsymbol{t})), \forall n \in \mathcal{P}$ and $C_n(\boldsymbol{x}'(\boldsymbol{t})) < C_n(\boldsymbol{x}^*(\boldsymbol{t}))$ for some $n \in \mathcal{P}$. This concludes the proof of the proposition. □

A two-step iterative algorithm was used to determine the Stackelberg equilibrium in the game Υ as shown in Algorithm 1. In the first step, the CES operator determines $\boldsymbol{\rho}$ that maximises (6.9) under constraints (4.4), (4.5), and (4.14) by using the CES energy trading strategies of the users $\mathcal{P}$. In the second step, the users $\mathcal{P}$ solve (4.10) using (4.12). To achieve the convergence of the algorithm, similar to [Atzeni et al., 2014], we adopt the termination criterion $\|\boldsymbol{\rho}^{(r)} - \boldsymbol{\rho}^{(r-1)}\|_2 / \|\boldsymbol{\rho}^{(r)}\|_2 \leq \tau$ where $\boldsymbol{\rho}^{(r)}$ represents $\boldsymbol{\rho}$ calculated at the iteration r.

The users' response in (4.12) is their optimal response at each time t for a given feasible $\boldsymbol{\rho}$ by the CES operator. This implies that, in Algorithm 1, the CES energy trading strategies of the users $\mathcal{P}$ will converge once $\boldsymbol{\rho}$ converges to a fixed point. Consequently, Algorithm 1 converges as the variation of $\boldsymbol{\rho}$ decreases after a certain number of iterations. Hence, Algorithm 1 converges approximately to a fixed point once the termination criterion is satisfied for sufficiently small τ.

4.5 Results and Discussion

For numerical simulations, we consider a residential community of 40 people with 30%, 40%, and 50% participating users. We obtain the average daily domestic PV power generation and user electricity demand profiles from [Jones et al., 2012]. We use $M = 48$, $\Delta t = 30$ min, $Q_M = 80$ kWh, $q(0) = 0.25Q_M$, $\alpha = 0.9^{1/48}$, $\beta^+ = 0.9$, $\beta^- = 1.1$ [Atzeni et al., 2014], and $\tau = 0.002$. Parameter ϕ_t is selected in each case such that $\phi_{\text{peak}} = 1.5 \times \phi_{\text{off peak}}$ where the peak period is 16:00-23:00. The value of ϕ_{peak} is then set such that the predicted daily unit price range of the grid is the same as a reference

Algorithm 1 Game to obtain the Stackelberg equilibrium

Step 1:

1: $r \leftarrow 1$.
2: **if** $r = 1$
3: The CES operator selects a feasible starting point for $\boldsymbol{\rho}$ and broadcasts it to the users $\mathcal{P}$.
4: **else**
5: The CES operator maximises (6.9) subject to constraints (4.4), (4.5), and (4.14) using $\tilde{\boldsymbol{X}}^*$ and broadcasts $\boldsymbol{\rho}$ to the users $\mathcal{P}$.
6: **end if**

Step 2:

7: Each user $n \in \mathcal{P}$ determines $\tilde{x}_n^*(t)$ at each time t using (4.12), and $\tilde{\boldsymbol{X}}^* = [\tilde{\boldsymbol{x}}^*\boldsymbol{(1)}^T, \cdots, \tilde{\boldsymbol{x}}^*\boldsymbol{(M)}^T]$ is announced to the CES operator.
8: $r \leftarrow r + 1$.
9: Repeat from 2 until $\|\boldsymbol{\rho}^{(r)} - \boldsymbol{\rho}^{(r-1)}\|_2 / \|\boldsymbol{\rho}^{(r)}\|_2 \leq \tau$.
10: Return $\tilde{\boldsymbol{X}}^*$ and $\boldsymbol{\rho}$ as the Stackelberg equilibrium.

time-of-use unit electricity price range used in Sydney, Australia [Ausgrid, 2014]. δ_t is a constant across time such that predicted average grid price matches the average price of the reference signal. To compare results, we consider a baseline energy trading system without a CES device where the users $\mathcal{P}$ trade energy exclusively with the main power grid that has the same energy cost model in Section 4.2.3. In particular, PV energy producers sell all surplus PV energy directly to the grid.

4.5.1 Performance of Algorithm 1

In this section, convergence of Algorithm 1 is examined. To show that Algorithm 1 converges to the theoretical optimum at the Stackelberg equilibrium of the fully-competitive CES model, we consider the optimisation (4.13) that gives the CES operator's theoretical optimum revenue at the Stackelberg equilibrium according to backward induction. Fig. 4.1 illustrates that Algorithm 1 reached the theoretical revenue of the CES operator within the first 2 iterations for 30% participating users. Here, as the initial conditions, $\boldsymbol{l}_{\boldsymbol{Q}}^{(1)}$ were considered as $\mathbf{0}$. Then, the elements of $\boldsymbol{a}^{(1)}$ were selected such that $\tilde{x}_n^*(t)$ values obtained using $\boldsymbol{l}_{\boldsymbol{Q}}^{(1)}$, $\boldsymbol{a}^{(1)}$, and (4.12) satisfy (6.5), (6.6), and (4.14). However, Algorithm 1 reached the termination criterion $\|\boldsymbol{\rho}^{(r)} - \boldsymbol{\rho}^{(r-1)}\|_2 / \|\boldsymbol{\rho}^{(r)}\|_2 \leq \tau$ after $r = 4$ iterations because the CES operator adjusts their strategy $\boldsymbol{\rho}$ until the termination criterion is achieved. Similarly, the algorithm converged after $r = 11$ and $r = 13$ iterations when the community has 40% and 50% participating users, respectively.

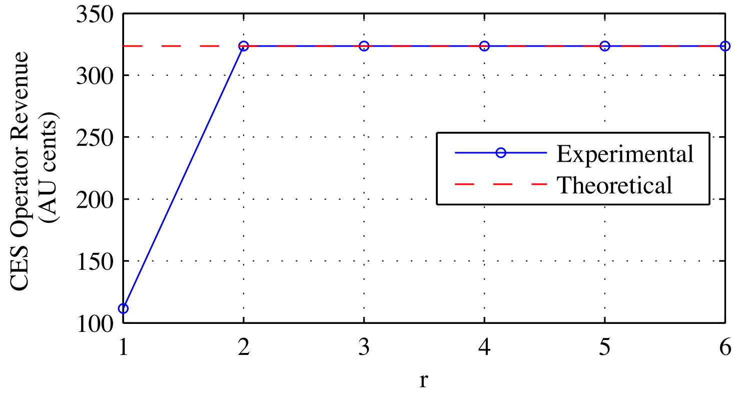

Fig. 4.1: Convergence of Algorithm 1 with 30% participating users in the fully-competitive CES model.

4.5.2 Preliminary Study of Three Energy Trading Systems

Consider the case with 40% participating users to demonstrate our CES models. In Fig. 4.2, we illustrate the variations of price signals of the CES operator and the grid in the fully-competitive CES model and the grid price of the baseline. Fig. 4.2 shows that the introduction of the CES device reduces the peak grid electricity price in the competitive CES model compared to the baseline. Before 09:00, when there is little PV energy and all participating users are deficit users, the CES operator sets a price above the equilibrium grid price such that it is unfavourable for any of the deficit users to purchase energy. Subsequently, the users $\mathcal{P}$ may not buy energy from the CES device during this period. During the day, when PV energy is plentiful, and through the evening peak, when electricity demand is greatest, it is favourable for the CES operator to trade energy with the users $\mathcal{P}$. Therefore, at these times the CES price approaches the equilibrium grid price in a similar way to the benevolent CES model. In turn, the users $\mathcal{P}$ transfer the majority of their energy transactions to the CES device. In the benevolent and the centralised cooperative CES models, there are more energy transactions between the CES device and

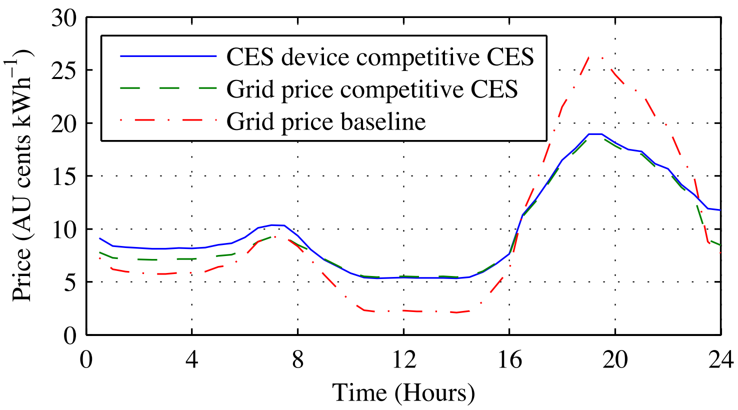

Fig. 4.2: Variation of electricity prices with 40% participating users in the fully-competitive CES model and the baseline.

the users $\mathcal{P}$ than in the fully-competitive CES model. Fig. 4.3 shows that this causes a greater reduction in the peak grid price.

More energy transactions between the CES device and the users $\mathcal{P}$ require greater CES storage capabilities (see Fig. 4.4), and subsequently, there are more energy transactions between the CES device and the grid: the fully-competitive case requires 58% less absolute energy traded between the CES device and the grid than the benevolent case.

Fig. 4.5 shows the sensitivity of community benefits of the three systems to CES battery capacity. The community benefit is the sum of absolute electricity cost savings of the users $\mathcal{P} \cup \mathcal{N}$ compared to the baseline and the CES revenue. As part of the CES revenue obtains from energy costs incurred by the users $\mathcal{P}$ (see (6.9)), the community benefit reflects the total reduction in costs paid by the community (all users and the CES operator) to the grid compared to the baseline. All models have optimal energy storage requirements corresponding to the peaks in Fig. 4.5. The fully-competitive CES model requires a battery capacity less than 70 kWh to provide peak community benefit compared to the other models. The centralised CES model considers load management of the entire community, not only the users $\mathcal{P}$, and therefore, requires a significantly larger storage capacity for optimal performance.

Table 4.1 compares the performance of the three systems over several metrics with different percentages of the users $\mathcal{P}$. Here, the percentage cost savings and the peak-to-average ratio reductions are calculated compared to the baseline. When combined with the CES inefficiencies and price signal limitations, the CES operator revenue reduces from the fully-competitive through benevolent to centralised case in each user-percentage case. Conversely, as the CES device enacts greater demand-side management by reducing the peak-to-average ratio, the average cost saving of a user in $\mathcal{P}$ increases. The average cost saving of a user in $\mathcal{P}$ is similar under the fully-competitive and benevolent CES models, then increases notably under the centralised CES model. In fairness point of view, the

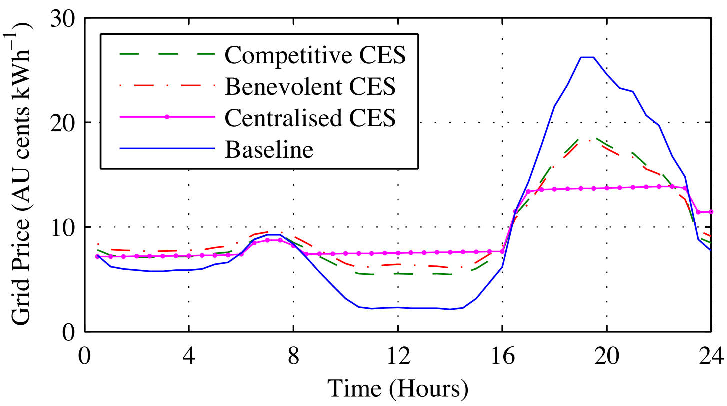

Fig. 4.3: Variation of grid electricity prices of the different CES operator models with 40% participating users.

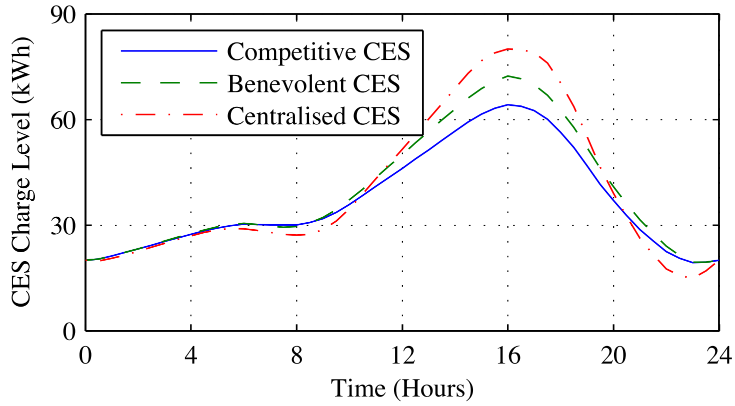

Fig. 4.4: Charge levels of the CES device for the different CES operator models with 40% participating users.

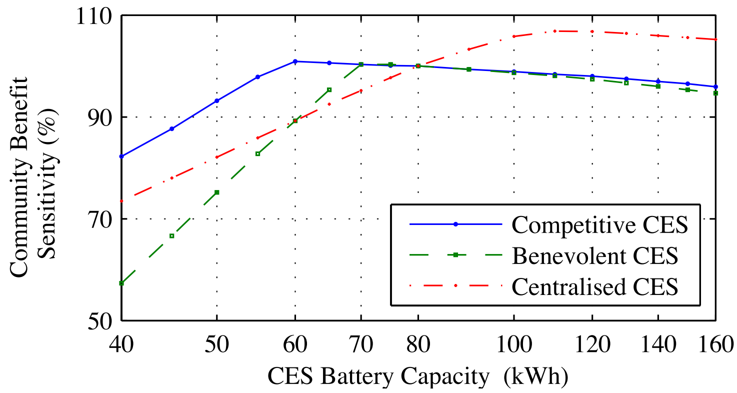

Fig. 4.5: Sensitivity of community benefit to energy storage capacity for the different CES operator models with 40% participating users.

Table 4.1: Performance of the three CES models with different fractions of participating users (PU). PAR is peak-to-average ratio.

Performance Metric	Average PU Cost Savings (%)			CES Operator Revenue (AU cents)			Community Benefit (AU cents)			PAR Reduction (%)		
PU Fraction	30%	40%	50%	30%	40%	50%	30%	40%	50%	30%	40%	50%
Competitive CES	27.6	29.4	31.4	323	344	373	945	1023	1123	30.3	31.7	33.1
Benevolent CES	30.7	32.4	34.9	229	191	160	856	852	889	33.8	35.9	38.3
Centralised CES	61.2	62.0	64.2	-22	-72	-150	1193	1267	1369	37.0	38.2	39.5

users $\mathcal{P}$ enjoy greater savings than the users $\mathcal{N}$. For example, with 40% participating users in the fully-competitive CES model, a participating user receives 29.4% cost saving on average and a non-participating user only receives 7.92% cost saving on average.

The CES revenue is greatest for the fully-competitive CES model and decreases significantly to a loss under the centralised CES model (see Table 4.1). This is because the fully-competitive model allows complete freedom to the CES operator to maximise revenue (4.13) while the benevolent CES operator is restricted to set a price and the centralised model eliminates the CES price signal. Overall, the total community benefit of introducing the CES device is greatest for the centralised CES followed by the fully-competitive CES and then the benevolent CES (see Table 4.1). On average, the fully-competitive CES model provides 81% of the centralised model's economic benefit compared with only 68% for the benevolent CES model. Overall, the fully-competitive system gives the best trade-off of cost benefits between the CES operator and the users $\mathcal{P}$ of the three systems while delivering significant load levelling.

Fig. 4.6 depicts the distribution of cost savings for individual participating users when the fully-competitive system has 30% participating users who have surplus energy distributions as shown in Fig. 4.7. According to the figures, the users those who have greater amount of surplus energy are more benefited by the system than the users with

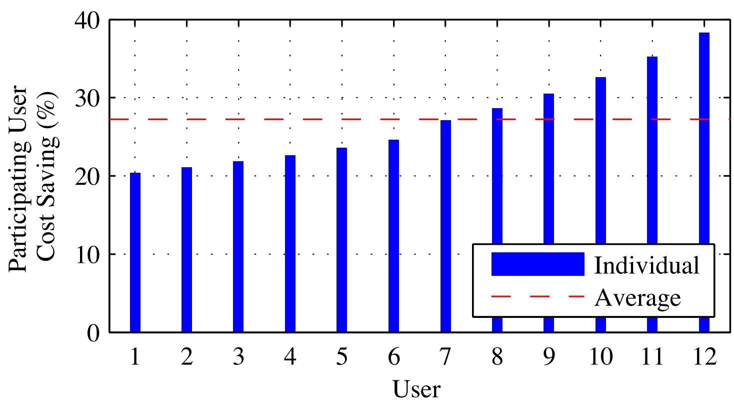

Fig. 4.6: Distribution of individual participating user cost savings with 30% users in the fully-competitive CES model.

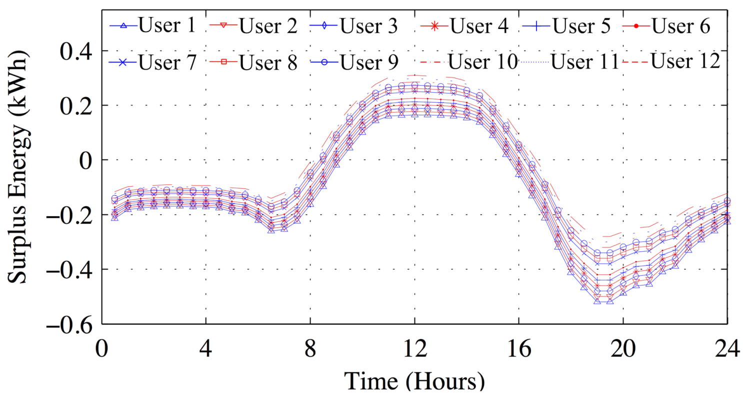

Fig. 4.7: Distribution of surplus energy of 30% participating users in the community.

less amount of surplus energy.

Having insights for the feasibility of the fully-competitive CES model, to investigate the effects of imperfect energy forecasts on the system, we introduce proportional variance white noise errors to the PV power and energy demand forecasts [Mediwaththe et al., 2016b]. When averaged over a large number of simulations, the mean absolute percentage energy forecast error is equal to half of percentage white noise variance. For 40% participating user case, when the mean absolute percentage forecast error changes from 0% to 50%, the average community user cost saving compared to the baseline was only reduced from 11.95% to 11.84%, and the average participating user saving was reduced from 29.37% to 29.21%. Here, for each 10% increase in mean absolute forecast error, the average community user cost saving decreased by nearly 0.02% while the average participating user cost saving declined by approximately 0.04%. Similar trends were observed for both 30% and 50% participating user cases. Therefore, the cost benefits of the fully-competitive CES model are robust to imperfect demand and PV energy forecasts.

4.6 Concluding Remarks

Community energy storage (CES) devices offer significant opportunities for user electricity cost savings, operator revenue, and peak-to-average ratio reduction of the grid. These benefits were shown to increase with the fraction of the participating users in the community. We have investigated three different CES operator models for community-level demand-side management and presented a fully-competitive CES model in a non-cooperative Stackelberg game that produces the best trade-off of operating environment between the CES operator and the users. Certainly, the proposed energy trading frameworks in this chapter and in Chapter 3 are based on day-ahead demand-side management where the energy trading strategies are determined a day in advance using photovoltaic (PV) energy and energy demand forecasts. In such scenario, it is important to explore the sensitivity of performance of the two energy trading systems to imperfect energy forecasts. In the next chapter, we carry out numerical performance analyses to investigate the impacts on the benefits of the two energy trading systems, anticipated by assuming accurate energy forecasts, when the provided energy forecasts are inaccurate.

Chapter 5

A Study of Impacts of Power Prediction Errors on the Energy Trading Systems

In this chapter, we numerically analyse the influences of photovoltaic (PV) energy and user demand forecasting errors on our proposed energy trading systems in Chapters 3 and Chapter 4 that accommodate day-ahead demand-side management.

5.1 Introduction

Day-ahead demand-side management is one of the common ways of performing energy management by today's electricity markets where the optimisation produces schedules of the energy management strategies of supply- and demand-side a day in advance. The advantage of day-ahead demand-side management is that it can induce energy users to efficiently plan their following day's energy consumption schedules and provide utility companies to estimate and plan energy amounts that need to be dispatched in the following day. Matching energy demand with supply has become one of the cumbersome tasks for power system operators with the rapid growth of renewable energy generation that is inherently uncertain and intermittent. Fig. 5.1 exemplifies the uncertainty of PV power generation by illustrating the variability between a two-days-ahead forecasted PV energy generation profile and the corresponding actual PV energy generation profile [Ela et al., 2013]. The challenge of balancing demand and supply has also been exacerbated with the randomness of energy consumption of end customers of the gird. At low-voltage level, higher forecasting errors could arise due to volatile noisy signals, for example, it is shown that the mean forecasting errors of user demand can be within $10\% - 20\%$ of actual energy profiles [Stephens et al., 2015]. On the one hand, the random, uncertain nature of both user

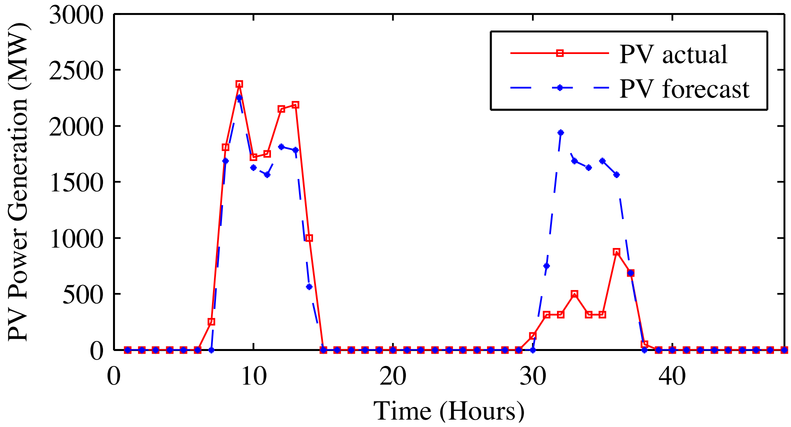

Fig. 5.1: An illustration of the variability between actual and forecasted PV energy generation [Ela et al., 2013].

energy demand and renewable energy production induces modifying day-ahead planned demand-side management strategies, which in turn incurs additional energy production costs for utility companies. On the other hand, if the same day-ahead determined strategies are adopted on the operating day, the anticipated benefits of demand-side management can be declined. Therefore, it is important to investigate the robustness of day-ahead demand-side management strategies against the potential imperfect information that occurs with inaccurate power forecast profiles.

In this thesis, the proposed game-theoretic energy trading systems are primarily intended to accommodate day-ahead demand-side management using forecasts of users' PV energy generation and demand profiles. For the tractability of the preliminary analyses of the performance of our game-theoretic frameworks, in the previous two chapters, we assumed that accurate predictions of the PV energy and demand profiles are available to users to determine their energy trading strategies. When the PV power and energy demand forecasts are inaccurate, the information available to the players in the non-cooperative games are imperfect and such situation leads to non-cooperative games with imperfect information with respect to environment. In this chapter, we attempt to numerically analyse the effects of imperfect information with respect to power forecasts on the performance of the energy trading systems discussed in the previous two chapters. To this end, we introduce errors into the energy forecasts so that the associated non-cooperative games are played with imperfect information. The chapter presents the following contributions:

- We show that the energy trading system in Chapter 3 is robust to both CES inefficiencies and prediction errors in users' day-ahead predicted energy demand and PV power generation profiles.

- We also demonstrate that the energy trading system in Chapter 4 is resilient to prediction errors related to day-ahead PV energy and demand forecasts as well as to significant range of prediction errors that could occur with continuous updates of power forecasts.

This remainder of this chapter is organised as follows. In Section 5.2, numerical analyses to study performance of the two energy trading systems in Chapter 3 and Chapter 4 are given. In particular, Section 5.2.1 demonstrates the performance of the energy trading system in Chapter 3 against day-ahead PV and demand forecast errors. Section 5.2.2 investigates the effect of day-ahead PV energy and demand forecast errors on the hierarchical fully-competitive energy trading system in Chapter 4. Section 5.2.3 extends the simulations in Section 5.2.2 to study the impact of power prediction errors, that could arise with continuous updates of PV energy and demand forecasts, on the hierarchical energy trading system. Section 5.3 concludes the chapter.

5.2 Performance of the Energy Trading Systems with Power Prediction Errors

5.2.1 Dynamic Game-theoretic Energy Trading System

In this section, we analyse the effects of CES battery inefficiencies and day-ahead forecast errors of PV energy and demand profiles of users on the energy trading system proposed in Chapter 3. As used for simulations in Chapter 3, we consider the same 40 user community with 30% participating users with all other parameters unchanged. Note that all the notations used in this section are as defined in Chapter 3. After CES leakage rate $\alpha = 0.95^{(1/48)}$, such that 1 kWh at the start of the day decays to 0.95 kWh at the end of the day, and charging inefficiencies $\beta^{+} = 0.95$, and $\beta^{-} = 1.05$ were introduced, the average participating user savings and average community user savings declined from 19.5% and 5.9% to 18.1% and 5.4%, respectively. Similarly, the peak-to-average ratio reduction declined from 9.7% to 9.0%. Hence 5% inefficiencies only cause a minor reduction in system performance. Similar results were obtained for 40% and 50% user cases.

To analyse the system performance against power forecasting errors, proportional variance white noise forecasting errors were also introduced to both the energy demand and PV energy generation forecasts of users to obtain actual power profiles [Stephens et al., 2015]. In particular, at each time $t \in T$, the day-ahead forecasted PV energy amount of each user $n \in \mathcal{P}$, $g_n^F(t)$, is related to their actual PV energy generation $g_n^A(t)$ such that

$$g_n^F(t) = g_n^A(t) + W \tag{5.1}$$

where $W = \omega\sigma g_n^A(t)$ is the white noise component in which ω is a random value chosen from the uniform distribution $[-1, 1]$, and σ is a constant that satisfies $0 \leq \sigma \leq 1$. Given (5.1) and for a particular value of σ, the mean absolute percentage forecasting error is equal to $\sigma \times \frac{100}{2}$ when averaged over $25,000$ simulations. Moreover, in simulations we consider that at each non-zero mean absolute percentage forecast error the users $\mathcal{P}$ follow their deterministic energy trading strategies evaluated at 0% forecast error. Under these circumstances, the system was extremely robust to uncorrelated white noise errors, where the errors for each person at each time were independent, showing negligible decrease in performance. However, since we are considering a localised community, consumer errors in PV forecasts are likely to be correlated at any given time. Therefore, when each of the energy demand and PV generation forecasts were fully correlated at each time, the average participating user savings, and average community user savings at 50% mean absolute prediction error declined from 18.1% and 5.4% to only 15.9% and 4.8%, respectively (see Fig. 5.2). Hence, the system performance is robust to extreme forecasting inaccuracies because, even with correlation effects, the CES approach aggregates enough people to mitigate the white noise errors. For comparison, under similar conditions except with household-distributed energy storages, all demand-side benefits evaporated above 30% mean absolute percentage error, above which the energy management system incurred increased costs for the community [Stephens et al., 2015].

5.2.2 Stackelberg Game-theoretic Energy Trading System

Having insights for the feasibility of the fully-competitive CES model in Chapter 4, here, we investigate the effects of imperfect day-ahead energy forecasts on the hierarchical fully-competitive energy trading system [Mediwaththe et al., 2016a]. For this purpose, we introduced proportional variance white noise errors to the day-ahead PV power and

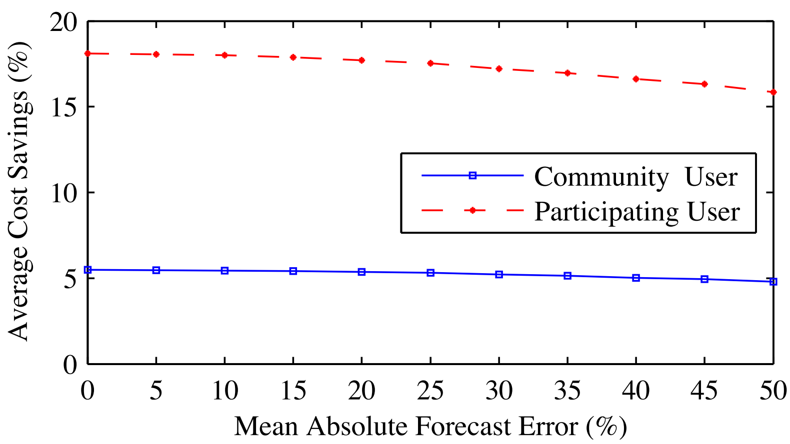

Fig. 5.2: Variation of average participating user and community user electricity cost savings with power prediction errors with 30% participating users in the community.

energy demand forecasts in the same way we used in Section 5.2.1. For 40% participating user case, when the mean absolute percentage forecast error changes from 0% to 50%, the average community user cost saving in the hierarchical energy trading system compared to the baseline (explained in Chapter 4) was only reduced from 11.9% to 11.8%, and the participating user saving was reduced from 29.4% to 29.2% on average. Similar trends were observed for both 30% and 50% participating user cases. Therefore, the cost benefits of the fully-competitive hierarchical energy trading system are robust to imperfect day-ahead demand and PV forecasts.

5.2.3 System Performance with Continuous Updates in Power Forecasts

It is regarded that the uncertainty of PV energy generation changes across multiple time scales [Ela and O'Malley, 2012]. In the previous sections, we analysed the performances of the energy trading systems by introducing forecast errors of single time-scale that is the impact of errors related to day-ahead PV energy and demand forecasts. In the real world, power forecasts can have continuous updates when the system reaches real time operation [Ela et al., 2013, Ela and O'Malley, 2012].

Considering this, in this section, we introduce power forecast errors that increase with time to reflect that forecasts of PV energy and demand profiles are updated at each time t. To this end, we consider the variance of the temporal percentage forecast error, $\left|\frac{g_n^F(t)-g_n^A(t)}{g_n^A(t)}\right| \times 100$, changes with time. Hence, at each time t, the random value ω in (5.1) is selected from uniform distributions that have different variances and zero mean across time. In summary, here, (5.1) is evaluated such that

$$g_n^F(t) = g_n^A(t) + \omega(t)\sigma g_n^A(t) \tag{5.2}$$

where the random value $\omega(t)$ at each time t is selected from uniform distributions that have different variances across time. In simulations, we selected uniform distributions that have increasing variances with time and the variance for each uniform distribution at each time t such that the mean absolute percentage forecast error is equal to $\sigma \times \frac{100}{2}$ with a large number of simulations. After introducing imperfect forecasts of PV energy and demand with finer time resolution, we investigate their effects on the benefits of the competitive hierarchical fully-competitive energy trading system in Chapter 4.

Fig. 5.3 depicts the temporal variations of energy costs of participating users in the hierarchical energy trading system for different mean absolute percentage forecast errors. Here, the system has 40% participating users in the community. The effect of the increasing mean absolute forecast error on the average energy costs of participating users is insignificant during off-peak times, whereas the average energy costs of the users during

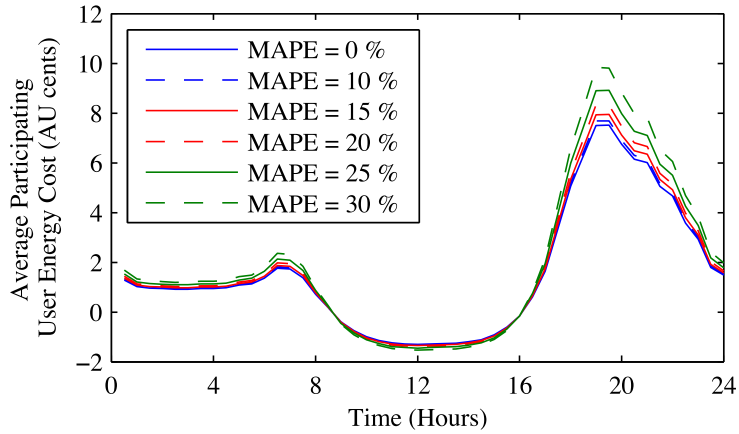

Fig. 5.3: Temporal variation of average energy costs of participating users with different mean absolute percentage errors (MAPEs) of power forecasts in the hierarchical energy trading system with 40% participating users.

peak hours increase with rising forecast errors (see Fig. 5.3). However, when considering the daily energy costs, the average cost savings of participating users and community users compared to the baseline system retain nearly unchanged up to significant mean absolute percentage forecast error as illustrated in Fig. 5.4.

5.3 Concluding Remarks

In this chapter, we numerically analysed the impacts forecast errors of PV energy generation and demand profiles on the two energy trading systems proposed in Chapter 3 and Chapter 4. Simulation analysis showed that the energy trading system in Chapter 3 is significantly resilient to inefficiencies of the CES device as well as to forecast errors in the day-ahead determined power profiles. Next, a similar analysis demonstrated that the benefits of the hierarchical fully-competitive energy trading system are resilient across

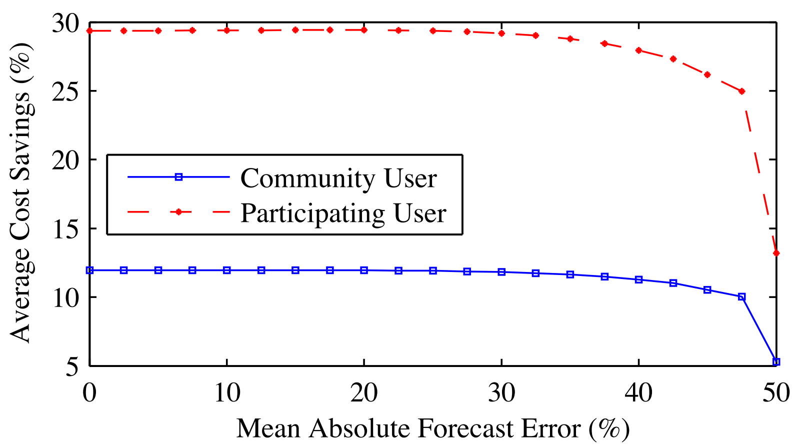

Fig. 5.4: Variation of average participating user and community user electricity cost savings with varying power prediction errors with 40% participating users in the hierarchical energy trading system.

significant range of forecast errors that could arise with continuous updates of PV energy and demand forecasts.

Similar to the importance of investigation of effects of energy forecast errors on demand-side management, it is also imperative to study the effects of non-ideal user behaviour on game-theoretic demand-side management. Successful demand-side management strategies require active user participation and the majority of existing game-theoretic approaches assume users will participate in demand-side management as long as their objectives are optimised. However, users might become irrational and non-ideal leading to unexpected outcomes of demand-side management. Due to this reason, in the next chapter, we investigate the effects of non-ideal actions of users on a game-theoretic bi-level energy trading system proposed for demand-side management of a residential community.

Chapter 6

Game-theoretic Hierarchical Energy Trading Robust to Non-ideal Energy User Behaviour

In this chapter, we study impacts of realistic and non-ideal participation time selection of users on a hierarchical energy trading system similar to the fully-competitive energy trading system proposed in Chapter 4. The non-ideal actions of the participating users with respect to choosing their energy trading start times are modelled using a prospect-theoretic approach. The performance of the energy trading system when the users' actions are non-ideal is compared with the outcomes obtained using conventional game-theoretic approach. Simulation results demonstrate that the energy trading system is robust to non-ideal time selection of the users.

6.1 Introduction

Demand-side management helps utilities to regulate increasing energy demand by utilising existing power grid infrastructure. Recent efforts of demand-side management include load-shifting methods, load curtailing methods and energy conservation strategies [Mohsenian-Rad et al., 2010]. Distributed energy resources such as energy storage devices and renewable energy resources provide vast opportunities for demand-side management by storing extra energy generated by renewable resources that can be dispatched to support peak energy demand.

In general, effectiveness of consumer-driven demand-side management methods depends on active participation of users. However, in the long run, users may change their participating behaviour leading to unexpected outcomes such as lower peak energy reduction and economic benefits. Therefore, designing successful demand-side management approaches have often been challenging with volatile user behaviour [Haney et al., 2011].

In this chapter, we investigate impacts of realistic energy user behaviour, which is not completely rational, on a decentralised energy trading system proposed to regulate electricity demand of a residential community. In the energy trading system, users with photovoltaic (PV) energy generation can decide to participate across time to trade energy with a community energy storage (CES) device. First, we elaborate a non-cooperative Stackelberg game to study the energy trading between the CES operator and participating users where the CES operator acts as the leader and the users are their followers. Then we develop another non-cooperative game between users to explore their behaviour in determining optimal energy trading starting times that minimise personal daily energy costs under two different user behavioural models: expected utility theory and prospect theory. The contributions of this work are:

- With time-varying subsets of active participating users that depend on their decisions of participating-time, the energy trading system attains a unique Stackelberg equilibrium across time where the CES operator maximises revenue while users minimise energy costs.
- Benefits of the energy trading system are robust to users' participating-time strategies that significantly deviate from complete rationality.

Game-theoretic demand-side management methods have been widely investigated in literature [Zhu et al., 2012a, Mohsenian-Rad et al., 2010, Atzeni et al., 2013a, Nguyen et al., 2012, Adika and Wang, 2014b, Yang et al., 2013]. These studies assume that users act rationally and ideally obeying the strategies predicted by game-theoretic systems. However, social studies have proved that the rationality assumption of game theory can be violated in real world when users face uncertainty in decision making [Kahneman and Tversky, 1979]. Abundant research using prospect theory has shown how real life user behaviour contravenes the conventional game theoretic rationality assumption [Wang et al., 2014, Wang and Saad, 2015]. In [Wang et al., 2015b], a prospect theoretic study for a load-shifting approach showed that deviations of users' decisions to participate from conventional game-theoretic decisions result in significantly different outcomes. In contrast to [Wang et al., 2015b], we apply prospect theory to study users' behaviour of choosing to participate across time in a Stackelberg game-theoretic energy trading system that does not intend to shift regular energy consumption of users. In this regard, we show that the outcomes of the energy trading system are indistinguishable under both prospect theory and expected utility theory, even though users' decisions to choose to participate differ between the two models. The Stackelberg game-theoretic energy trading system between a CES device and users in Chapter 4 assumes users participate from the beginning of day and hence the number of users remain consistent over time. Here, we extend the Stackelberg energy trading system to study users' decisions of selecting energy trading starting times incorporating prospect theory. The CES-user Stackelberg game in this chapter differs from that in Chapter 4 because the number of active participating users is time-variant depending upon each user's decision of choosing an energy trading starting time.

The remainder of the chapter is organised as follows. Section 6.2 describes system configuration including demand-side model and energy storage model used for the energy trading system.

6.2 System configuration

6.2.1 Demand-side Model

The community consists of two types of energy users: participating users $\mathcal{P}$ ($|\mathcal{P}| = I$) and non-participating users $\mathcal{N}$. The users $\mathcal{P}$ have rooftop PV panels and they are the players in the energy trading optimisation who trade energy with the grid and the CES device. The users $\mathcal{N}$ are conventional grid users without behind-the-meter energy generation and are not players in the energy trading optimisation. Depending on net PV energy after consuming, the users $\mathcal{P}$ are classified into surplus users $\mathcal{S}(t)$ and deficit users $\mathcal{D}(t)$ those are time-dependent. For the energy trading optimisation, the entire control time period $\mathcal{T}$, usually a day, is partitioned into M number of equal time slots with granularity of Δt. We assume that PV power generation and demand forecasts of the following day are available to the users $\mathcal{P}$ to decide their day-ahead energy trading strategies. If $g_n(t)$ and $e_n(t)$ are the PV energy and the regular energy demand of user $n \in \mathcal{P}$ at time $t \in \mathcal{T}$, respectively, then they sell/buy energy amount $x_n(t)$ to/from the CES device at time t such that

$$x_n(t) = l_n(t) + (g_n(t) - e_n(t)) \tag{6.1}$$

where $l_n(t)$ is the grid energy consumption of the user. Note that $l_n(t) > 0$ when the user buys energy from the grid and $l_n(t) < 0$ when the user sells energy to the grid. If the surplus energy of the user n is $s_n(t) = g_n(t) - e_n(t)$, each user $i \in \mathcal{S}(t)$ sells energy to the CES device and user $j \in \mathcal{D}(t)$ buys energy from the CES device such that

$$\begin{aligned} 0 \leq x_i(t) \leq s_i(t), \\ s_j(t) \leq x_j(t) \leq 0. \end{aligned} \tag{6.2}$$

6.2.2 Energy Storage Model

The CES operator trades $l_Q(t)$ energy with the grid at each time t where $l_Q(t) > 0$ (< 0) if the CES device is charged (discharged). Here, we use the same CES model given in Chapter 4 that is similar to the energy storage model in [Atzeni et al., 2013a]. In this regard, per-slot energy trading amounts are given as $x_n(t) = x_n(t)^+ - x_n(t)^-$ and $l_Q(t) = l_Q(t)^+ - l_Q(t)^-$ where $x_n(t)^+$ and $l_Q(t)^+$ are the per-slot charging energy amounts, and $x_n(t)^-$ and $l_Q(t)^-$ are the per-slot discharging energy amounts. We define a charging efficiency $0 < \beta^+ \leq 1$, a discharging efficiency $\beta^- \geq 1$ and a leakage rate $0 < \alpha \leq 1$ for the energy storage. Denoting $q(0)$ is the charge level at the beginning of day, the energy capacity limit of the CES device gives

$$\mathbf{0} \prec q(0)\boldsymbol{\eta} + \Psi\left[\boldsymbol{\chi}^+, -\boldsymbol{\chi}^-\right]\boldsymbol{\beta} \preceq \boldsymbol{Q_M} \tag{6.3}$$

where $\boldsymbol{Q_M} \in \Re^{M\times 1}$ with elements of maximum energy capacity of the CES device Q_M. $\boldsymbol{\eta} \in \Re^{M\times 1}$ with elements $[\boldsymbol{\eta}]_v = \alpha^v$ and the (v, w) entry of the lower triangular matrix $\boldsymbol{\Psi} \in \Re^{M\times M}$ is $[\Psi]_{v,w} = \alpha^{v-w}$. $\boldsymbol{\beta} = [\beta^+, \beta^-]^T$, $\mathbf{0}$ is the $M \times 1$ zero matrix and $\boldsymbol{\chi}^+, \boldsymbol{\chi}^- \in \Re^{M\times 1}$ with elements $\chi^+ = \sum_{n=1}^{I}(x_n(t)^+ + l_Q(t)^+)$, $\chi^- = \sum_{n=1}^{I}(x_n(t)^- + l_Q(t)^-)$, respectively.

We define (6.4) to ensure the continuity of the CES device operation of the following day and to avert its over-charging or over-discharging across $\mathcal{T}$ such that

$$q(0) = q(M) \tag{6.4}$$

where $q(M)$ is the charge level at the end of day. Readers are referred to Chapter 4 for detailed description of the CES model.

6.2.3 Energy Cost Models

The pricing mechanism of the grid is similar to [Mohsenian-Rad et al., 2010] and in particular the unit energy price at time t depends on the total load on the grid at time t, $L(t) = \sum_{n=1}^{I} l_n(t) + L_{\mathcal{N}}(t) + l_Q(t)$ where $L_{\mathcal{N}}(t)$ is the total grid load of the users $\mathcal{N}$. Then at time t, the unit energy price of the grid is

$$p(t) = \phi_t L(t) + \delta_t, \tag{6.5}$$

where $\phi_t > 0$ and $\delta_t > 0$. The CES operator also adopts a unit energy price $a(t)$ for their energy transactions with the users $\mathcal{P}$ such that any user $n \in \mathcal{P}$ receives $a(t)x_n(t)$ from the CES operator for their selling energy $x_n(t)$. Then the energy cost of the user $n \in \mathcal{P}$ at time t is

$$C_n(t) = p(t)l_n(t) - a(t)x_n(t). \tag{6.6}$$

The CES operator obtains a revenue from the energy trading with the users $\mathcal{P}$ and the grid that is given by

$$R = \sum_{t=1}^{M}\big(- a(t)\sum_{n\in\mathcal{P}} x_n(t) - p(t)l_Q(t)\big). \tag{6.7}$$

Here, we assume that the energy trading between the CES operator and the grid uses the energy rate of the grid.

6.3 Energy Trading Stackelberg game

In the energy trading system, the CES operator maximises their revenue in (6.7) by choosing optimal $a(t)$ and $l_Q(t)$. Following the strategies of the CES operator, each user $n \in \mathcal{P}$ is supposed to minimise their energy cost in (6.6) at each time $t \in \mathcal{T}$ by determining optimal $x_n(t)$. Based on contractual agreements with the system owners, the users $\mathcal{P}$ can individually choose a time $h_n \in \{1, 2, \cdots, M\}$ to start energy trading with the system such that their total daily energy cost is minimised (this process is explained in Section 6.4). After participating at h_n, they continue to trade energy for $h_n \leq t \leq M$. Given the opportunity to choose energy trading starting times, the number of active participating users at each time t may not be uniform, and we denote the number of active participating users at time t is $I(t) = |\mathcal{P}(t)| \leq I$ where $\mathcal{P}(t) \subset \mathcal{P}$.

6.3.1 Participating Users-Side Analysis

Using the pricing signal $\boldsymbol{a} = [a(1), \cdots, a(M)]^T$ and the grid energy trading profile $\boldsymbol{l_Q} = [l_Q(1), \cdots, l_Q(M)]^T$ broadcasted by the CES operator, the users $\mathcal{P}(t)$ at each time $t \in [1, \cdots, H]$ minimise their personal energy costs in (6.6). Let us consider a single time slot t where $I(t) \geq 2$[1]. Then for user $k \in \mathcal{P}(t)$, the cost function (6.6) is quadratic with respect to $x_k(t)$

$$C_k(t) = \omega_1 x_k(t)^2 + \omega_2 x_k(t) + \omega_3 \tag{6.8}$$

where $\omega_1 = \phi_t$, $\omega_2 = (\phi_t(L_{-k}(t) - 2s_k(t)) + \delta_t - a(t))$ and $\omega_3 = (\phi_t s_k(t)(s_k(t) - L_{-k}(t)) - \delta_t s_k(t))$ using (6.1) and (6.5). Here, $L_{-k}(t)$ is the total grid energy load at time t excluding the load of the user k and $L_{-k}(t) = \sum_{k' \in \mathcal{P} \setminus k} l_{k'}(t) + l_{\mathcal{N}}(t) + l_Q(t)$. Clearly, (6.8) is interdependent on each other's behavior and we study the energy trading coordination between the users $\mathcal{P}(t)$ using a non-cooperative game $G \equiv \langle \mathcal{P}(t), \mathcal{X}, \mathcal{C} \rangle$. Here, $\mathcal{X} = \{\boldsymbol{X_1(t)}, \cdots, \boldsymbol{X_k(t)}, \cdots, \boldsymbol{X_{I(t)}(t)}\}$ is the strategy set available to the users $\mathcal{P}(t)$ and $\boldsymbol{X_k(t)}$ is the strategy set of the user k subject to (6.2). $\mathcal{C}$ is the set of cost functions given by $\mathcal{C} = \{C_1(t), \cdots, C_k(t), \cdots, C_{I(t)}(t)\}$.

Each user $k \in \mathcal{P}(t)$ determines the optimal energy trading amount from $\boldsymbol{X_k(t)}$ such that their energy cost $C_k(x_k(t), \boldsymbol{x_{-k}(t)}) \equiv C_k(t)$ is minimised. Here, $\boldsymbol{x_{-k}(t)}$ denotes the strategy profile of the opponents of the user k that is given by $\boldsymbol{x_{-k}(t)} = \{x_1(t), \cdots x_{k-1}(t), x_{k+1}(t) \cdots, x_{I(t)}(t)\}$. Then the optimisation problem of each user $k \in \mathcal{P}(t)$ is to find

$$\tilde{x}_k(t) = \underset{x_k(t) \in \boldsymbol{X_k(t)}}{\operatorname{argmin}} \; C_k(x_k(t), \boldsymbol{x_{-k}(t)}). \tag{6.9}$$

[1] $I(t) = 1$ implies that there is a single active user who minimises their energy cost without a game among users $\mathcal{P}$.

Note that the game G is similar to the non-cooperative subgame between users in Chapter 4. However, the subsets of players $\mathcal{P}(t)$ are not uniform for the game G played at each time $t \in \mathcal{T}$ in contrast to Chapter 4. Although the number of players is time-variant, using the same rationale in Chapter 4 we can prove that the game G played at any particular time t has a unique Nash equilibrium for any feasible $a(t)$ and $l_Q(t)$. At the Nash equilibrium of the game G, the optimal energy trading amount of the user k, $\tilde{x}_k^*(t)$ can be found by setting the first derivative of (6.8) with respect to $x_k(t)$ to zero that gives

$$\frac{\partial C_k(t)}{\partial x_k(t)} = 2\omega_1 \tilde{x}_k(t) + \omega_2 = 0. \tag{6.10}$$

Solving (6.10) for all users $\mathcal{P}(t)$ simultaneously, we can obtain

$$\tilde{x}_k^*(t) = s_k(t) + \gamma(t) \tag{6.11}$$

where $\gamma(t) = (I(t)+1)^{-1}({\phi_t}^{-1}(a(t) - \delta_t) - l_{\mathcal{N}}(t) - l_Q(t))$.

6.3.2 CES Operator-Side Analysis

The CES operator also maximises their revenue in (6.7) by determining optimal $\boldsymbol{\rho} = [\boldsymbol{a},\ \boldsymbol{l_Q}]$. By substituting (6.11) in (6.7), we can write the objective of the CES operator as

$$\boldsymbol{\rho} = \underset{\boldsymbol{\rho} \in \mathcal{Q}}{\operatorname{argmax}} \sum_{t=1}^{M} (\lambda_1 a(t)^2 + \lambda_2 a(t) + \lambda_3 l_Q(t)^2 + \lambda_4 l_Q(t)) \tag{6.12}$$

where $\lambda_1 = -I(t)(I(t)+1)^{-1}{\phi_t}^{-1}$, $\lambda_2 = I(t)(I(t)+1)^{-1}(l_{\mathcal{N}}(t) + {\phi_t}^{-1}\delta_t) - \sum_{k=1}^{I(t)} s_k(t)$, $\lambda_3 = -\phi_t(I(t)+1)^{-1}$, and $\lambda_4 = -(I(t)+1)^{-1}(\phi_t l_{\mathcal{N}}(t) + \delta_t)$. $\mathcal{Q}$ is the strategy set available to the operator subject to (6.3) and (6.4). There is a unique solution for the objective function of the CES operator, since (6.12) is strictly concave because of the negative definite Hessian matrix with respect to all feasible $\boldsymbol{a}$, $\boldsymbol{l_Q}$ and the strategy set $\mathcal{Q}$ is convex due to linear constraints (6.3) and (6.4).

6.3.3 Stackelberg Equilibrium

The CES operator first sets optimal $\boldsymbol{\rho}$ to maximise (6.7) and broadcasts them to the users $\mathcal{P} \equiv \{\mathcal{P}(1) \cup \cdots \cup \mathcal{P}(M)\}$. Then the users $\mathcal{P}(t)$ at each time $t \in \mathcal{T}$ follow these signals to find optimal $x_k(t)$ by playing the game G. We model this hierarchical interaction between the CES operator and the users $\mathcal{P}$ using a non-cooperative Stackelberg game Υ. In the game Υ, *players* are the CES operator and the users $\mathcal{P}$ where the CES operator is the leader and the users $\mathcal{P}$ are the followers. As the *strategies*, the CES operator determines $\boldsymbol{\rho} \in \mathcal{Q}$ to maximise (6.7) and at time t, user $k \in \mathcal{P}(t)$ selects $x_k(t) \in \boldsymbol{X_k(t)}$ to minimise cost in (6.6). The *utilities* are as defined in (6.7) for the CES operator and (6.6) for the user $k \in \mathcal{P}(t)$.

Definition 6. *Let $\boldsymbol{\rho}^*$ be the solution of* (6.12) *and $\boldsymbol{X}^* \equiv \{[\boldsymbol{x}^*\boldsymbol{(1)}]^T, \cdots, [\boldsymbol{x}^*\boldsymbol{(M)}]^T\}$ where $\boldsymbol{x}^*\boldsymbol{(t)}$ be the solution of the game G at time $t \in \mathcal{T}$. Then the point $[\boldsymbol{\rho}^*, \boldsymbol{X}^*]$ is a Stackelberg equilibrium if and only if*

$$R(\boldsymbol{X}^*, \boldsymbol{\rho}^*) \geq R(\boldsymbol{X}^*, \boldsymbol{\rho}),\ \forall \boldsymbol{\rho} \in \mathcal{Q}, \tag{6.13}$$

$$\begin{aligned} &C_k(\boldsymbol{x}^*\boldsymbol{(t)},\ \boldsymbol{\rho}^*) \leq C_k(x_k(t), \boldsymbol{x_{-k}(t)}, \boldsymbol{\rho}), \\ &\forall k \in \mathcal{P}(t),\ \forall x_k(t) \in \boldsymbol{X_k(t)},\ \forall t \in \mathcal{T}. \end{aligned} \tag{6.14}$$

Proposition 6. *The game Υ has a unique Stackelberg equilibrium.*

Proof. The game G played at any time t has a unique Nash equilibrium for feasible $a(t)$ and $l_Q(t)$. Further, the revenue maximisation of the CES operator in (6.12) has a unique solution. Hence, the game Υ converges to a unique Stackelberg equilibrium once the CES operator obtains optimal strategy $\boldsymbol{\rho}^*$ while the users $\mathcal{P}$ attain their H-tuple of unique Nash equilibrium solutions $\boldsymbol{X}^*$. □

6.4 Participation-Time Selection Game

Before the Stackelberg game in Section 6.3 takes place, the users $\mathcal{P}$ individually select optimal times h_n to start energy trading such that their total daily energy costs are minimised. Similar to [Wang et al., 2015b], to explicitly study such user behaviour with respect to choosing to participate across time in our system, we develop a non-cooperative game Ξ between the users $\mathcal{P}$ that has the strategic form $\Xi = \langle \mathcal{P}, \boldsymbol{K}, \boldsymbol{U} \rangle$ and study it under expected utility theory and prospect theory. Here, $\boldsymbol{K}$ is the set of available strategies to the users $\mathcal{P}$ i.e., energy trading starting times. $\boldsymbol{K} = \{\boldsymbol{K}_n\}_{n \in \mathcal{P}}$ where $\boldsymbol{K}_n = \{1, \cdots, M\}$; $\forall n \in \mathcal{P}$. $\boldsymbol{U} = \{U_n\}_{n \in \mathcal{P}}$ is the set of cost functions that captures the daily energy costs for each user $n \in \mathcal{P}$. Note that the Stackelberg equilibrium described in Section 6.3 depends on temporal distribution of the users $\mathcal{P}(t)$ which is a result of how the users $\mathcal{P}$ begin energy trading across time. At the Stackelberg equilibrium corresponding to an action (i.e., energy trading starting time) profile $\boldsymbol{h} = \{h_n, \boldsymbol{h}_{-n}\} = \{h_1, \cdots, h_I\}$ of the users $\mathcal{P}$ where $h_n \in \boldsymbol{K}_n$, the daily energy cost of user n, U_n is equivalent to

$$U_{n,\boldsymbol{h}} = \sum_{t=1}^{H} p^*_{\boldsymbol{h}}(t) l^*_{n,\boldsymbol{h}}(t) - a^*_{\boldsymbol{h}}(t) x^*_{n,\boldsymbol{h}}(t). \tag{6.15}$$

Here, $p^*_{\boldsymbol{h}}(t),\ a^*_{\boldsymbol{h}}(t),\ l^*_{n,\boldsymbol{h}}(t),\ x^*_{n,\boldsymbol{h}}(t)$ are the grid price, CES energy price, user n's grid load and their CES energy trading amount at the Stackelberg equilibrium obtained for $\boldsymbol{h}$, respectively. Note that $\boldsymbol{h}_{-n}$ is the action profile of the users $\mathcal{P}$ except user n. In the game Ξ, each user $n \in \mathcal{P}$ chooses an energy trading starting time h_n for given $\boldsymbol{h}_{-n}$ such that their energy cost in (6.15) is minimised.

Remark 1. *After the users $\mathcal{P}$ decide to participate as per optimal energy trading starting times determined by playing the game Ξ, the Stackelberg energy trading in Section 6.3 takes place that ultimately achieves a Stackelberg equilibrium.*

In the long run, the users $\mathcal{P}$ may change their behaviour with respect to choosing an energy trading starting time. Hence, we investigate a solution for the non-cooperative game Ξ that captures empirical frequencies of actions followed by the users $\mathcal{P}$. The straightforward interpretation is that each user $n \in \mathcal{P}$ assigns a probability for each action in $\boldsymbol{K}_n$. In such a paradigm, users face uncertainty to make decisions and we characterise solutions for the game Ξ based on mixed strategies under two different user behavioural models: expected utility theory and prospect theory.

6.4.1 Energy Trading Under Expected Utility Theory

Under the notion of mixed strategies, each user $n \in \mathcal{P}$ determines the optimal probability distribution over the actions in $\boldsymbol{K}_n$ to minimise expected daily energy cost. Here, we explore how the users $\mathcal{P}$ decide probabilities of energy trading starting times according to expected utility theory assuming that all users make rational choices by objectively viewing their opponents' behaviour. According to the theory, the expected daily energy cost of the user n can be given as

$$E_n^{EUT}(\boldsymbol{y}) = \sum_{\boldsymbol{h} \in \boldsymbol{K}} U_{n,\boldsymbol{h}} \prod_{m=1}^{I} y_m(h_m), \tag{6.16}$$

where $\boldsymbol{y} = \{\boldsymbol{y}_n, \boldsymbol{y}_{-n}\}$, $\boldsymbol{y}_n = [y_n(1), \cdots, y_n(M)]$ and $y_m(h_m)$ is the probability of choosing h_m by the user m. $\boldsymbol{y}_{-n}$ is the probabilities of the users $\mathcal{P}$ except user n.

The intuition behind the cost in (6.16) relies on the assumption that the user n assesses their neighbours' empirical frequencies of actions identical to their objective probabilities of choosing actions. However, this generalisation may not be valid in the real world as people overweight outcomes with low probabilities and underweight outcomes with high probabilities. These observations are clearly explained under prospect theory [Kahneman and Tversky, 1979].

6.4.2 Energy Trading Under Prospect Theory

In practice, the users $\mathcal{P}$ may subjectively evaluate their neighbours' actions to minimise energy costs. This characteristic is more realistic than assuming users act rationally and perceive their neighbours' behaviour objectively [Kahneman and Tversky, 1979]. In this regard, we study actual user behaviour as to when they select their energy trading starting time using prospect theory.

To this end, probability weighting functions are used to model the subjective behaviour of users when they make decisions under risk and uncertainty. In this regard, the probability weighting function $w_n(y)$ implies the subjective evaluation of the user n about an outcome with y probability. We use the Prelec function [Prelec, 1998] to model the subjective perceptions of users on each other's behaviour that is given by

$$w_n(y) = \exp(-(-\ln y)^{\kappa_n});\ 0 < \kappa_n \leq 1. \tag{6.17}$$

Here, κ_n is a parameter that decreases as the user's subjective evaluation deviates from the objective probability. If the user's subjective and objective probabilities are equal, then $\kappa_n = 1$ and this corresponds to expected utility theory. Assuming that the subjective probabilities of user $n \in \mathcal{P}$ about their own actions are equal to their objective probabilities, the expected daily energy cost of user n under prospect theory is

$$E_n^{PT}(\boldsymbol{y}) = \sum_{\boldsymbol{h} \in \boldsymbol{K}} U_{n,\boldsymbol{h}} y_n(h_n) \Big(\prod_{m \in \mathcal{P} \setminus n}^{I-1} w_n(y_m(h_m)) \Big). \tag{6.18}$$

6.4.3 ϵ-Nash Equilibria

After defining the expected daily costs of the users $\mathcal{P}$, we now analyse the solutions for the game Ξ played under expected utility theory and prospect theory. Due to computational usefulness [Brown and Shoham, 2008], here we study the existence of $\epsilon-$Nash equilibria. For the game Ξ, a mixed strategy profile $\boldsymbol{y^*} \equiv \{\boldsymbol{y}_n^*, \boldsymbol{y}_{-n}^*\}$ is an $\epsilon-$Nash equilibrium if it satisfies

$$E_n(\boldsymbol{y}_n^*, \boldsymbol{y}_{-n}^*) \leq E_n(\boldsymbol{y}_n, \boldsymbol{y}_{-n}^*) + \epsilon;\ \forall \boldsymbol{y}_n \in \mathcal{Y}_n, \forall n \in \mathcal{P}, \tag{6.19}$$

where $\mathcal{Y}_n$ is the set of all mixed strategy profiles over $\boldsymbol{K_n}$ and $\epsilon > 0$. In general, $\epsilon-$Nash equilibria always exist [Brown and Shoham, 2008] and for the game Ξ, we are interested to find ϵ-Nash equilibrium located close to a mixed strategy Nash equilibrium under both expected utility theory and prospect theory. We use the iterative algorithm proposed in [Wang et al., 2015b] that was proved to converge to an ϵ-Nash equilibrium close to a mixed strategy Nash equilibrium under both expected utility theory and prospect theory. In summary, the algorithm is given by

$$\boldsymbol{y}_n^{(r+1)} = \boldsymbol{y}_n^{(r)} + \frac{\nu}{r}(\boldsymbol{d}_n^{(r)} - \boldsymbol{y}_n^{(r)}), \tag{6.20}$$

where r is the iteration number, $0 < \nu < 1$ is the inertia weight. $\boldsymbol{d}_n^{(r)} = \{d_n^{(r)}(h_{n,1}), \cdots, d_n^{(r)}(h_{n,M})\}$ of which

$$d_n^{(r)}(h_{n,t}) = \begin{cases} 1,\ \text{if } h_{n,t} = \underset{h_n \in \boldsymbol{K}_n}{\operatorname{argmin}}\, c_n(h_n, \boldsymbol{y}_{-n}^{(r-1)}), \\ 0,\ \text{otherwise}, \end{cases} \tag{6.21}$$

where $c_n(h_n, \boldsymbol{y}_{-n}^{(r-1)})$ is the expected cost when the user n selects the pure strategy h_n in response to the mixed strategies of other players at iteration $(r-1)$ i.e., $\boldsymbol{y}_{-n}^{(r-1)}$. Note that for prospect theory, $\boldsymbol{y}_{-n}^{(r-1)}$ considers the weighted probabilities of other users' mixed strategies at $(r-1)$.

Remark 2. *As the algorithm converges, ϵ-Nash equilibrium with respect to strategy profile $\boldsymbol{y}$ is obtained under both expected utility theory and prospect theory.*

Given the equilibrium probabilities of participating-time decisions of the users $\mathcal{P}$, we can define the expected revenue of the CES operator under both prospect theory and expected utility theory. In this regard, if $\boldsymbol{y}_{EUT}^*$ and $\boldsymbol{y}_{PT}^*$ are the ϵ-Nash equilibriums under expected utility theory and prospect theory, respectively, then the subsequent expected daily CES revenue R^{EXP} in each case can be obtained by

$$R^{EXP} = \sum_{\boldsymbol{h}\in\boldsymbol{K}} R(\boldsymbol{h}) \prod_{m=1}^{I} y_m^*(h_m), \tag{6.22}$$

where $R(\boldsymbol{h})$ is the CES revenue as per (6.7) at the Stackelberg equilibrium corresponds to $\boldsymbol{h}$, $y_m^*(h_m) \in \boldsymbol{y}_{EUT}^*$ for expected utility theory and $y_m^*(h_m) \in \boldsymbol{y}_{PT}^*$ for prospect theory.

6.5 Simulation Results

In simulations, we consider real data of average PV power and user demand of the Western Power Network in Australia on a summer day [Jones et al., 2012] (see Fig. 6.1), and we assume that all users have power profiles same to these average profiles. Further, $M = 24$, $\Delta t = 1$h, $Q_M = 80$ kWh, $q(0) = 20$ kWh, $\alpha = 0.9^{(1/48)}$, $\beta^+ = 0.9$ and $\beta^- = 1.1$ [Atzeni et al., 2013a]. Peak hours of the grid are between 16.00 and 23.00, and we select ϕ_t such that $\phi_{\text{peak}} = 1.5\ \phi_{\text{off-peak}}$. We choose ϕ_{peak} such that the predicted grid price range is same to the reference time-of-use price range in [Ausgrid, 2014] and δ_t is set to a

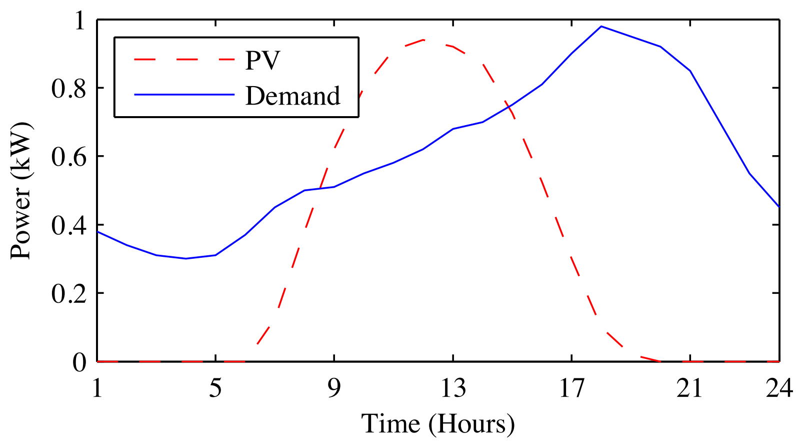

Fig. 6.1: Average PV power and user electricity demand.

constant such that the average predicted grid price is equal to the average reference price. The community has 10 households where 6 users are participating users $\mathcal{P}$ in the system. The allowable energy trading starting times for the users $\mathcal{P}$ are 01.00, 12.00 and 17.00 so that $\boldsymbol{K}_n = \{1, 12, 17\}$. For comparisons, we use a baseline without a CES device where the users $\mathcal{P}$ trade energy directly with the grid that uses the same energy cost model. For the algorithm, we use $\boldsymbol{y}_n^{(0)} = [0.3, 0.3, 0.4]$; $\forall n \in \mathcal{P}$ and $\nu = 0.7$.

Fig. 6.2 illustrates expected cost savings of the users $\mathcal{P}$ under expected utility theory, and under prospect theory for three different $\kappa \in (0, 1]$ (i.e., 0.7, 0.4 and 0.1) assuming $\kappa_n = \kappa$; $\forall n \in \mathcal{P}$. Note that from (6.17), as κ tends to 0 users become more subjective deviating from the objective evaluation assumption in expected utility theory. Here, cost savings are calculated compared to the baseline. When $\kappa = 0.7$, and even when $\kappa = 0.4$ with significant non-ideal behaviour, the expected cost savings remained almost 28% under both models because for all users, participation probabilities at each time in $\boldsymbol{K}_n$ using prospect theory do not significantly deviate from those obtained under expected utility theory as shown in Table 6.1. When $\kappa = 0.1$, the participation probabilities at $h_n = 1$

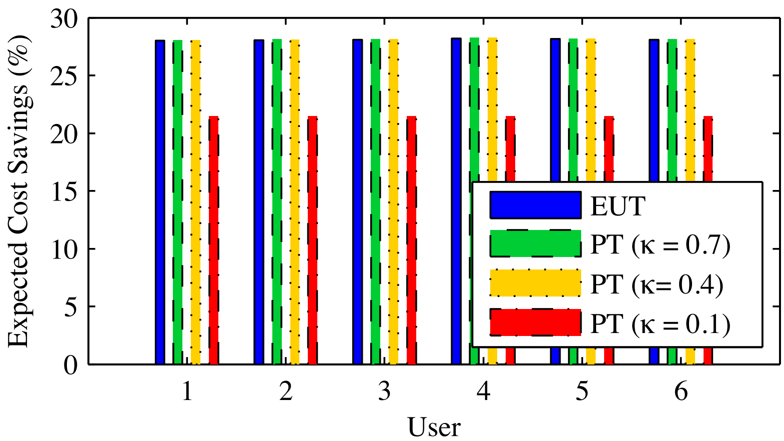

Fig. 6.2: Expected user cost savings under expected utility theory (EUT) and prospect theory (PT).

Table 6.1: Participation Probabilities of users $\mathcal{P}$ for $h_n \in \boldsymbol{K}_n \equiv \{1, 12, 17\}$ when $\kappa = 0.7,\ 0.4,\ 0.1$

User	EUT			PT ($\kappa = 0.7$)			PT ($\kappa = 0.4$)			PT ($\kappa = 0.1$)		
	$h_n = 1$	$h_n = 12$	$h_n = 17$	$h_n = 1$	$h_n = 12$	$h_n = 17$	$h_n = 1$	$h_n = 12$	$h_n = 17$	$h_n = 1$	$h_n = 12$	$h_n = 17$
1	0.9966	0.0005	0.0029	0.9988	0.0005	0.0007	0.9989	0.0005	0.0006	0.9979	0.0009	0.0012
2	0.9966	0.0005	0.0029	0.9988	0.0005	0.0007	0.9989	0.0005	0.0006	0.9979	0.0009	0.0012
3	0.9966	0.0005	0.0029	0.9988	0.0005	0.0007	0.9989	0.0005	0.0006	0.9979	0.0009	0.0012
4	0.0070	0.9924	0.0006	0.0076	0.9918	0.0006	0.0070	0.9924	0.0006	0.9979	0.0009	0.0012
5	0.0070	0.0005	0.9925	0.0076	0.0005	0.9919	0.0095	0.0005	0.9900	0.9979	0.0009	0.0012
6	0.9966	0.0005	0.0029	0.9988	0.0005	0.0007	0.9989	0.0005	0.0006	0.9979	0.0009	0.0012

are significantly increased for the fourth and fifth users compared to those predicted using expected utility theory (see Table 6.1). As a result, the expected cost savings reduced from 28% to 21.5% for all users.

Fig. 6.3, Fig. 6.4, and Fig. 6.5 depict the variations in different aspects of system performance across the range of possible κ values. Here, larger κ tending to 1 reflects that

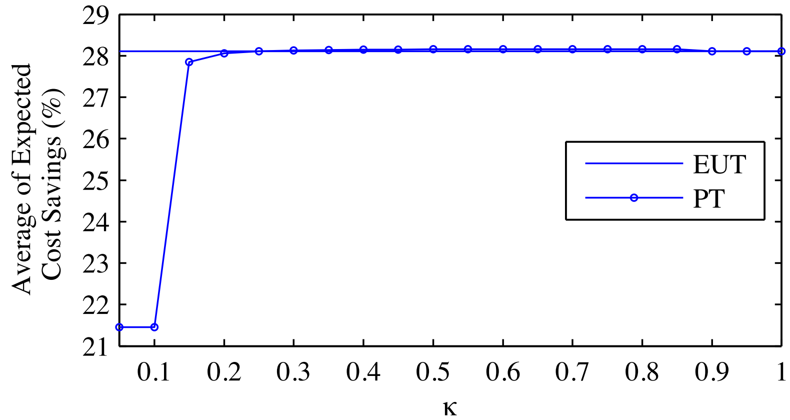

Fig. 6.3: Average of expected user cost savings with different κ.

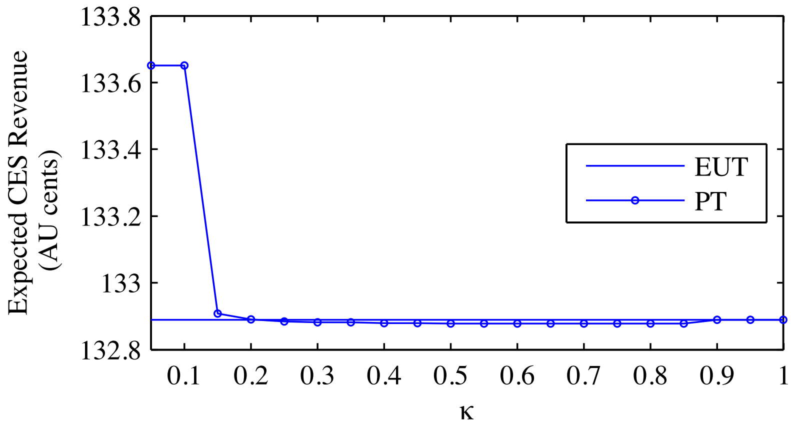

Fig. 6.4: Expected CES operator revenue with different κ.

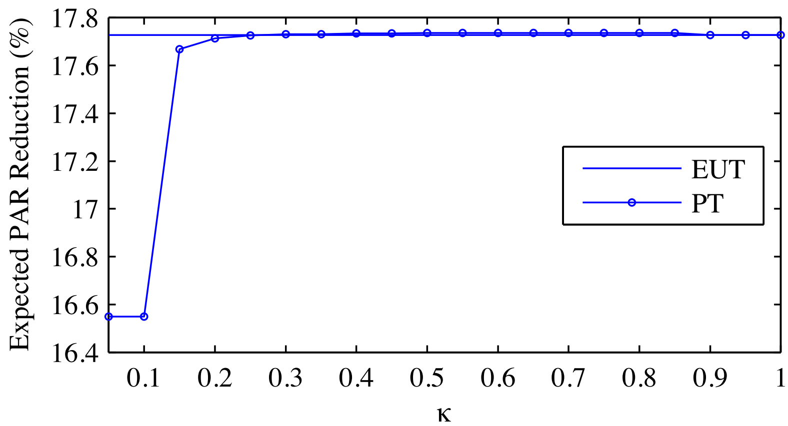

Fig. 6.5: Expected peak-to-average ratio (PAR) reduction with different κ.

the users behave closer to the rationality assumption in expected utility theory, and smaller κ tending to 0 implies that their evaluations of opponents' actions are more distorted from that of expected utility theory. Fig. 6.3 shows that under expect utility theory, the average of expected cost savings of the users achieved by participating in the system is 28.1%. On the other hand, even if the users' weighting effects on their opponents' actions are getting larger, i.e., when κ is getting smaller, the expected cost savings will not significantly fluctuate and remain almost at 28% except for $0 < \kappa \leq 0.1$. Fig. 6.4 shows that, when $\kappa > 0.15$, expected revenue for the CES operator retains nearly unchanged compared to the expected revenue calculated under expected utility theory. In terms of demand-side management of the grid, the expected peak-to-average ratio reduction compared to the baseline will not change notably from the peak-to-average ratio reduction predicted using expected utility theory when $\kappa > 0.15$. This is because as shown in Table 6.1, for $\kappa > 0.15$, users' prospect theoretic probabilities of participation at each time remain almost the same as those in expected utility theory. When $0 < \kappa \leq 0.1$, the fourth and fifth users will more likely to start energy trading from the beginning under prospect theory, which is not the case under expected utility theory. However, this behavioural change will only reduce the expected peak-to-average ratio reduction from 17.7% to 16.55% (see Fig. 6.5).

6.6 Concluding Remarks

In this chapter, we studied the effects of realistic, non-ideal behaviour of users, with respect to choosing energy trading starting times, on a game-theoretic energy trading system between a community energy storage (CES) device and users. First, we developed a non-cooperative Stackelberg game to study the energy trading interaction between the users and the CES operator based on users' decisions as to whether to participate across time. Next we studied a non-cooperative game to explore how the users make decisions to participate in the above energy trading system under two user behavioural models: prospect theory and expected utility theory. Simulation results demonstrated that the benefits of the energy trading system are robust to users' participating time strategies that deviate from complete rationality. We postulate that the energy trading system can be scaled to any number of participating users and present similar performance trends.

Certainly, non-ideal user behaviour would also have impacts on electric vehicle charging management methods that involve complex interactions among electric vehicle owners or electric vehicle aggregators that regulate charging of electric vehicle fleets. Motivated by the prospect-theoretic analysis of this chapter, in the next chapter, we examine a non-cooperative electric vehicle charging competition among electric vehicle aggregators while accounting for the aggregators' potential non-ideal actions.

Chapter 7

Electric Vehicle Charging Management Robust to Non-ideal User Behaviour

In this chapter, we study a coordinated electric vehicle (EV) charging competition among multiple EV aggregators while accounting for the aggregators' non-ideal actions that are not completely rational. The EV charging competition is modelled by developing a non-cooperative game among the aggregators which is then studied under prospect theory to incorporate the aggregators' subjective behaviour. The chapter concludes with an extensive performance analysis that investigates the effects of non-ideal actions of the aggregators on the coordinated EV charging benefits of the system.

7.1 Introduction

Escalating fuel prices and environmental concerns have increased the market penetration of electric vehicles (EVs) worldwide. For example, a recent study [Block et al., 2015] has shown that the annual growth rate of EV sales in the United States is more than 20%. Despite environment-friendly features, uncoordinated EV charging creates challenges to both economical and technical aspects of the power grid as a consequence of excessive load consumption. Due to the escalation in electricity demand provoked by EVs, demand-side management has become a paramount element in power system operation as it can decrease EV charging costs by coordinating the grid-to-vehicle operation economically. EV aggregators have been widely adopted in the present energy market with the aim of facilitating coordinated charging of EVs at large scale. An EV aggregator acts as a middleman, between a fleet of EVs and the power grid, to optimally regulates the charging plan of the vehicle fleet so as to minimise overall cost of EV charging considering EV charging constraints [Wu et al., 2012, Hu et al., 2016].

Effective demand-side management of grid-to-vehicle operation requires active participation of users who are either vehicle owners or EV aggregators that seek to optimise individual goals through coordinated EV charging. However, in the long run, users might deviate from their ideal participating behaviour despite the benefits that they gain through participating in demand-side management. Unpredictable non-ideal behaviour of users is likely to compromise the economic benefits and system efficiencies of demand-side management. A successful energy management approach for EV charging is often challenging with inconsistent user behaviour [Franke and Krems, 2013].

In this chapter, the EV charging competition among multiple EV aggregators in a coordinated EV charging system is studied while accounting for non-ideal actions of the aggregators that are not completely rational. Each aggregator determines EV charging start time and charging energy profiles to minimise EV charging energy cost by considering the actions of the neighbouring EV aggregators. The interactions among the EV aggregators are modelled using a non-cooperative game-theoretic framework, which is then studied under two user behavioural models, expected utility theory and prospect theory, to incorporate aggregators' ideal and non-ideal actions in selecting EV charging start times in the EV charging competition. The main contributions of this chapter can be stated as follows.

- We model the coordinated EV charging competition among the EV aggregators as a two-stage non-cooperative game and show that there exists a subgame perfect ϵ-Nash equilibrium when the game is played with either ideal, or non-ideal actions, of the aggregators.

- We analyse the impacts of potential non-ideal actions of the EV aggregators through an extensive performance analysis and show that the benefits of the coordinated EV charging strategy, in terms of peak-to-average ratio reductions and EV charging cost savings, are resilient to non-ideal actions taken by the aggregators.

Prospect theory has emerged as an important tool to examine non-ideal user behaviour that departs from the rational choices in game theory. To the best of our knowledge, few works related to demand-side management have applied prospect theory to study non-ideal, realistic behaviour of participants that cannot be explained by assuming consumer rationality [Wang et al., 2015b, Mediwaththe and Smith, 2016a]. For example, [Wang et al., 2015b] elaborates insights from prospect theory to study realistic consumer decision-making in a load-shifting demand response program for residential households. In [Mediwaththe and Smith, 2016a], prospect theory is used to study the user behaviour in a Stackelberg game-theoretic energy trading system between a community energy storage device and photovoltaic energy users. Due to the inherent differences in system models and associated constraints between the EV charging scenario and the residential load-shifting and bi-level energy trading systems, the prospect theory-based analyses in [Wang et al., 2015b, Mediwaththe and Smith, 2016a] cannot be directly applied to the EV charging scenario considered in this chapter. Furthermore, to the best of our knowledge, in literature, the effects of non-ideal actions of participating users on an EV charging scenario have not been investigated using prospect theory in literature.

The remainder of this chapter is organised as follows. Section 7.2 describes the EV charging system configuration, and Section 7.3 describes the two-stage non-cooperative game among the EV aggregators. Section 7.4 elaborates the non-cooperative EV charging energy determination game among the aggregators and Section 7.5 discusses the participation time selection game of the aggregators. Section 7.6 presents numerical results and Section 7.7 concludes the chapter.

7.2 System Configuration

This section describes the formulation of the system models of EV aggregators and the cost models that are used to derive energy costs in this chapter.

7.2.1 Electric Vehicle Charging Model

In this chapter, a low-voltage power grid with multiple EV aggregators distributed along the grid is considered. Here, an EV aggregator acts as an intermediary between the power grid and a fleet of EVs and regulates and schedules charging of the connected EVs considering EV charging constraints. In this work, only grid-to-vehicle operation with unidirectional power flow is considered.

In the system model, the set of EV aggregators is denoted as $\mathcal{M}$ and $|\mathcal{M}| = N$. Each aggregator $i \in \mathcal{M}$ controls an EV charging station that consists of multiple EV chargers within a localised geographical area. For example, such charging stations may be located in car parks at workplaces, universities, and shopping centres. In this case, each aggregator i regulates charging of a set of EVs $\mathcal{B}_i$ over a set period of time $\mathcal{T}$ and $|\mathcal{B}_i| = V_i$. In this chapter, it is assumed that the EVs in $\mathcal{B}_i$ are charged through aggregator i, and the vehicles are parked at the charging station for the entire time period of $\mathcal{T}$. Such a scenario can be expected at an EV charging station where EVs are parked for a long period of time such as nighttime EV charging or workplace EV charging scenarios where there is an agreement between the EV owners and the aggregators. In such situations, the aggregators, which may be run by car park managers, can coordinate EV charging efficiently to charge EVs within the considered time period $\mathcal{T}$. At the end of time period $\mathcal{T}$, it is required to charge all EVs in $\mathcal{B}_i$ to their maximum state-of-charge (SOC) limits. This work assumes that additional EVs will not join the set $\mathcal{B}_i$ during the time period $\mathcal{T}$ similar to the EV charging framework considered in [Richardson et al., 2012]. The charging horizon $\mathcal{T}$ is divided into M number of time slots of Δt length and the control time is denoted by $t \in \{1, 2, \cdots, M\}$.

Without loss of generality, it is considered that there is a base load profile $\boldsymbol{L}_b$ on the grid that is not time-flexible and $\boldsymbol{L}_b$ is given by

$$\boldsymbol{L}_b = (L_{b,1}, \cdots, L_{b,t}, \cdots, L_{b,M}) \tag{7.1}$$

where $L_{b,t}(> 0)$ is the base grid load at time t. For example, $\boldsymbol{L}_b$ may constitute non-deferrable loads of users of the grid. From the utility's perspective, $L_{b,t}$ represents the minimum load that the utility should provide at time t.

For each aggregator i, there is an energy demand E_i that is equal to the total energy demands of the EVs in $\mathcal{B}_i$. The energy demand of an EV $n \in \mathcal{B}_i$ is given by

$$e_n = S_{n,\text{init}} - S_{n,\text{max}} \tag{7.2}$$

where $S_{n,\text{init}}$ and $S_{n,\text{max}}$ are the SOC level at the beginning of $\mathcal{T}$ and maximum SOC level of the battery of EV n, respectively. Using (7.2), E_i can be written as $E_i = \sum_{n=1}^{V_i} e_n$. In the EV charging model, each aggregator i supplies energy E_i to the EVs in $\mathcal{B}_i$ by distributing it across time $\mathcal{T}$. In this situation, the temporal grid energy consumption profile of aggregator i over the time period $\mathcal{T}$ is given by

$$\boldsymbol{x}_i = (x_{i,1}, \cdots, x_{i,t}, \cdots, x_{i,M}) \tag{7.3}$$

where $x_{i,t}$ is the energy amount taken from the grid by aggregator i at time t.

To consider conversion losses of EV chargers controlled by aggregator i, a charging efficiency parameter η_i is introduced such that $0 < \eta_i \leq 1$. For example, if $x_{i,t}$ amount of energy is taken from the grid by aggregator i, only $\eta_i x_{i,t}$ amount is effectively dispatched for charging EVs in $\mathcal{B}_i$. Given (7.3) and η_i, E_i of each aggregator i satisfies

$$E_i = \sum_{t=1}^{M} \eta_i x_{i,t}. \tag{7.4}$$

It is considered that each EV $n \in \mathcal{B}_i$ is charged using a charging rate between a maximum charging rate R_n and a minimum charging rate taken as zero at time t [Richardson et al., 2012, Clement-Nyns et al., 2010]. This gives

$$0 \leq r_{n,t} \leq R_n \tag{7.5}$$

where $r_{n,t}$ is the charging rate of EV $n \in \mathcal{B}_i$ at time t. Considering (7.5) for all EVs in $\mathcal{B}_i$, energy consumption $x_{i,t}$ satisfies

$$0 \le \frac{\eta_i x_{i,t}}{\Delta t} \le \sum_{n=1}^{V_i} R_n. \tag{7.6}$$

In this chapter, it is assumed that the total power demand of aggregators at each time t can be obtained from the grid without violating the grid voltage and capacity constraints.

7.2.2 Energy Cost Models

In this chapter, a dynamic grid cost function that consists of both real time and time-of-use pricing elements is considered [Mohsenian-Rad et al., 2010]. Given the total grid load as $L_t = L_{b,t} + \sum_{i=1}^{N} x_{i,t}$, the grid cost function at time t is given as

$$P_t(L_t) = \phi_t L_t^2 + \delta_t L_t \tag{7.7}$$

where ϕ_t and δ_t are positive time-of-use tariff constants at time t. The cost function (7.7) can be regarded as a quadratic function that approximates piecewise linear pricing models adopted by some electric utility companies [Mohsenian-Rad et al., 2010, Li, 2007]. By incorporating time-of-use and real time pricing components with these cost models, users can be encouraged to shift their peak demand to non-peak hours [Mohsenian-Rad et al., 2010, Zhu et al., 2015, Yu and Hong, 2016b]. According to (7.7), per unit electricity price of the grid at time t, p_t, is given as $p_t = \phi_t L_t + \delta_t$, and the resulting grid energy cost of aggregator i at time t is given by $p_t x_{i,t}$.

In addition to the grid energy cost, another cost function $D_{i,t}$ is defined for each aggregator i that depends on the deviation between their actual energy consumption and the target energy consumption at time t [Jiang and Low, 2011]. Denoting the target energy consumption of aggregator i at time t as $\bar{x}_{i,t}$, $D_{i,t}$ is given by

$$D_{i,t} = \begin{cases} g_{i,t}(\bar{x}_{i,t} - x_{i,t})^2, & \text{if } 0 \le x_{i,t} < \bar{x}_{i,t}, \\ 0, & \text{if } x_{i,t} \ge \bar{x}_{i,t} \end{cases} \tag{7.8}$$

where $g_{i,t}(> 0)$ is a parameter that varies among the aggregators $\mathcal{M}$ at each time t and represents how each aggregator i weighs the deviation between their actual energy consumption $x_{i,t}$ and the target energy consumption at each time t.

In this framework, if aggregator i charges EV $n \in \mathcal{B}_i$ using maximum charging rate R_n, then they require e_n/R_n number of time slots to reach $S_{v,\max}$ from $S_{v,\text{init}}$. It is assumed that if aggregator i starts EV charging at time slot $t_i \in \{1, 2, \cdots, M\}$, then they continue the charging process for $t_i \le t \le M$. For instance, if aggregator i starts charging the EVs in $\mathcal{B}_i$ at time slot 3, then the aggregator determines $(x_{i,3},\ x_{i,4}, \cdots,\ x_{i,M})$ such that

$E_i = \sum_{t=3}^{T} \eta_i x_{i,t}$. Given this assumption and if aggregator i charges each EV $n \in \mathcal{B}_i$ using their maximum charging rate R_n, then the aggregator requires λ_i time slots to finish charging all EVs in $\mathcal{B}_i$ where

$$\lambda_i = \max(e_1/R_1,\ e_2/R_2, \cdots,\ e_{V_i}/R_{V_i}). \tag{7.9}$$

Since aggregator i can vary the charging rates of each EV in $\mathcal{B}_i$ according to (7.5), λ_i represents the minimum number of time slots that aggregator i requires to charge all EVs in $\mathcal{B}_i$. This implies that for a given λ_i, aggregator should start EV charging at least from time slot $\tilde{t}_i$ where $\tilde{t}_i = (M - \lambda_i) + 1$. Hence, aggregator i can start EV charging between time slot 1 and $\tilde{t}_i$. Then, the set of all possible EV charging start times $\mathcal{I}_i$ of aggregator i can be written as $\mathcal{I}_i = \{1, 2, \cdots, \tilde{t}_i\}$ where $\mathcal{I}_i \subseteq \{1, 2, \cdots, M\}$. If aggregator i starts the EV charging process at time slot $t_i \in \mathcal{I}_i$, then their total energy cost is given by

$$C_i = \sum_{t=t_i}^{M} (p_t x_{i,t} + D_{i,t}). \tag{7.10}$$

7.3 Two-stage Non-cooperative Game

To analyse how each aggregator i determines their EV charging start time t_i and EV charging energy amounts $x_{i,t}$ at each time t, a two-stage non-cooperative game Ω among the aggregators $\mathcal{M}$ is developed. At the first stage of the game Ω, the aggregators $\mathcal{M}$ non-cooperatively determine their EV charging start time $t_i \in \mathcal{I}_i$ with imperfect information [Brown and Shoham, 2008]. After observing how the aggregators have selected $t_i \in \mathcal{I}_i$ at the first stage, each aggregator i non-cooperatively determines $x_{i,t}$ with imperfect information at the second stage.

Since each aggregator i has $|\mathcal{I}_i|$ number of possible actions in total at the first stage of the game Ω, the extensive form of the game Ω implies that at the second stage, the game Ω has $K = (|\mathcal{I}_1| \times |\mathcal{I}_2| \times \cdots \times |\mathcal{I}_N|)$ number of proper subgames [Fudenberg and Tirole, 1991]. It is considered that the set of proper subgames at the second stage are as $\Psi = \{G_1,\ G_2, \cdots, G_K\}$. Then the game Ω has $(K+1)$ number of subgames including the entire game itself. In this chapter, the strategic form of the game Ω is described as follows.

- *Players*: The set of aggregators $\mathcal{M}$.
- *Strategies*: Each aggregator i selects $(t_i, \boldsymbol{x}_i)$ to maximise their payoff. In particular, at the first stage, each aggregator i determines $t_i \in \mathcal{I}_i$. Then at the second stage, depending on the selected t_i at the first stage, each aggregator i determines $\boldsymbol{x}_i = (x_{i,t_i}, x_{i,t_i+1}, \cdots, x_{i,M})$ such that $\boldsymbol{x}_i \in \mathcal{X}_i$ where $\mathcal{X}_i$ subject to constraints (7.4) and (7.6).

- *Payoffs*: For an action profile $(t_i, \boldsymbol{x}_i)$, aggregator i receives a payoff

$$U_i = -C_i = -\sum_{t=t_i}^{M} (p_t x_{i,t} + D_{i,t}). \tag{7.11}$$

To determine the solutions of the game Ω, first, the optimal solutions for each subgame in Ψ at the second stage are evaluated. Then the analysis proceeds backwards to the first stage where each aggregator i determines optimal $t_i \in \mathcal{I}_i$ that maximises their payoffs, which results if the optimal actions determined for each subgame in Ψ are adopted by the aggregators $\mathcal{M}$ at the second stage. The explicit analyses of these two steps are given in the next two sections.

7.4 Second Stage Game: Charging Energy Determination Game

This section explains the process of determining EV charging energy amounts by each aggregator i once they have selected to start EV charging from time slot $t_i \in \mathcal{I}_i$. Let $G_\sigma \in \Psi$ be the subgame among the aggregators $\mathcal{M}$ at the second stage if they adopt an EV charging start time profile $\boldsymbol{\sigma} = (t_1, t_2, \cdots, t_N) \in \mathcal{I}$ at the first stage of the game Ω. Here, $\mathcal{I}$ denotes the cartesian product of strategy sets $\mathcal{I}_i$ of the aggregators $\mathcal{M}$ that is given by $\mathcal{I} = \{\mathcal{I}_1 \times \mathcal{I}_2 \times \cdots \times \mathcal{I}_N\}$. Because each aggregator i continues EV charging for $t_i \leq t \leq M$ once they have selected to start EV charging at time t_i, in the game G_σ, each aggregator i seeks to maximise their individual payoff given in (7.11). In this scenario, their individual decisions on $x_{i,t}$ are influenced by each others' energy consumption decisions due to the aggregate load dependency of the grid price p_t. The strategic form of the game G_σ is given as follows.

- *Players*: The set of aggregators $\mathcal{M}$.
- *Strategies*: Each aggregator i determines $\boldsymbol{x}_i \in \mathcal{X}_i$ to maximise payoff.
- *Payoffs*: Each aggregator i receives a payoff given by (7.11).

In the game G_σ, each aggregator i solves the local optimisation problem to determine

$$\tilde{\boldsymbol{x}}_i = \underset{\boldsymbol{x}_i \in \mathcal{X}_i}{\operatorname{argmax}}\ U_i(\boldsymbol{x}_i, \boldsymbol{x}_{-i}) \tag{7.12}$$

where $U_i(\boldsymbol{x}_i, \boldsymbol{x}_{-\boldsymbol{i}}) \equiv U_i$ and $\boldsymbol{x}_{-i}$ is the EV charging energy profile of the other aggregators $i' \in \mathcal{M} \backslash i$.

Proposition 7. *The game G_σ has a unique pure strategy Nash equilibrium.*

Proof. For a given $\boldsymbol{x}_{-i}$, the objective function in (7.12) is strictly concave with respect to $\boldsymbol{x}_i$ as its Hessian matrix with respect to $\boldsymbol{x}_i$ is negative definite. Moreover, the strategy set $\mathcal{X}_i$ of each aggregator i is non-empty, compact, and convex due to linearity of (7.4) and (7.6). Therefore, the game G_σ is a concave N-person game and has a pure strategy Nash equilibrium [Rosen, 1965]. Moreover, that Nash equilibrium is unique as the objective function and the strategy sets in (7.12) satisfy Theorem 2 in [Rosen, 1965]. □

The Nash equilibrium of the game G_σ is denoted by $\boldsymbol{x}^* = (\boldsymbol{x}_1^*, \boldsymbol{x}_2^*, \cdots, \boldsymbol{x}_N^*)$. In this chapter, $\boldsymbol{x}^*$ is approximated using the iterative best-response algorithm given in Algorithm 2. The algorithm terminates when the relative distance of $\boldsymbol{x}$ between two consecutive iterations is very small, for example, $\|\boldsymbol{x}^{(r)} - \boldsymbol{x}^{(r-1)}\|_2 / \|\boldsymbol{x}^{(r)}\|_2 \leq \tau$ where τ is a very small positive value and r is the iteration number.

Algorithm 2 Game to obtain the Nash Equilibrium of the game G_σ

1: Using EV charging start time t_i, randomly initialise $\boldsymbol{x}_i$ for each aggregator i such that $\boldsymbol{x}_i \in \mathcal{X}_i$ and set $r \leftarrow 0$.
2: **while** termination criterion is not satisfied **do**
3: Set $r \leftarrow r + 1$.
4: **for** each aggregator i **do**
5: Aggregator i solves (7.12) and determines $\tilde{\boldsymbol{x}}_i$ using the temporal aggregate grid load vector, excluding i's load, $\boldsymbol{L}_{-i}^{(r-1)} = \left(L_{t_i,-i}^{(r-1)}, \cdots, L_{t,-i}^{(r-1)}, \cdots, L_{M,-i}^{(r-1)}\right)$ at the previous iteration $r-1$. Here, $L_{t,-i}^{(r-1)} = L_t^{(r-1)} - x_{i,t}^{(r-1)}$.
6: **end for**
7: **end while**
8: **return** The Nash equilibrium $\boldsymbol{x}^*$.

7.5 First Stage Game: Participation Time Selection Game

In this section, the selection of optimal EV charging start times of the aggregators $\mathcal{M}$ at the first stage of the game Ω is described. Note that, since the solution analysis of the game Ω moves backwards, the game at the first stage has a payoff for its each action profile $\boldsymbol{\sigma} \in \mathcal{I}$ equals to the Nash equilibrium payoff obtained for its corresponding subgame $G_\sigma \in \Psi$ at the second stage. Let Φ denote the non-cooperative game among the aggregators $\mathcal{M}$ at the first stage that has payoffs equivalent to the Nash equilibrium payoffs of subgames Ψ at the second stage. Explicitly, the game Φ can be described as follows.

- *Players*: The set of aggregators $\mathcal{M}$.
- *Strategies*: Each aggregator i determines $t_i \in \mathcal{I}_i$ to maximise payoff.

- *Payoffs*: If the aggregators' EV charging start time profile is $\boldsymbol{\sigma} \in \mathcal{I}$, then each aggregator i receives a payoff given by

$$F_i(\boldsymbol{\sigma}) = -\sum_{t=t_i}^{M} p_t^*(\boldsymbol{\sigma}) x_{i,t}^*(\boldsymbol{\sigma}) + D_{i,t}^*(\boldsymbol{\sigma}) \tag{7.13}$$

  where $p_t^*(\boldsymbol{\sigma})$ and $x_{i,t}^*(\boldsymbol{\sigma})$ are the unit grid price and the EV charging energy amount of aggregator i at time t obtained at the Nash equilibrium of the game G_σ, respectively. Furthermore, $D_{i,t}^*(\boldsymbol{\sigma})$ is the cost given in (7.8) after obtaining the Nash equilibrium of the game G_σ.

Let $\boldsymbol{\sigma}_{-i}$ denote the EV charging start time strategy profile of all aggregators $\mathcal{M}$ excluding aggregator i. Then in the game Φ, each aggregator i maximises the payoff given in (7.13) by determining the optimal t_i for a given $\boldsymbol{\sigma}_{-i}$.

Proposition 8. *A Nash equilibrium strategy profile of the game Φ leads to a subgame perfect Nash equilibrium of the game Ω.*

Proof. The proof of the proposition immediately follows intuitions of backward induction [Fudenberg and Tirole, 1991]. In particular, when considering the extensive form (tree form) of the two-stage game Ω, the game Φ is the reduced game of the game Ω after eliminating all subgames Ψ at the second stage by assigning their Nash equilibrium outcomes to the outcomes after the first stage of the game Ω. For example, with respect to the strategy profile $\boldsymbol{\sigma} \in \mathcal{I}$, the payoff of each aggregator i in (7.13) is defined by assuming that the aggregators $\mathcal{M}$ will play the Nash equilibrium of the corresponding subgame G_σ at the second stage. Therefore, a Nash equilibrium of the game Φ leads to a subgame perfect Nash equilibrium of the game Ω. □

Remark 3. *Once the aggregators $\mathcal{M}$ have determined their optimal EV charging start time profile $\boldsymbol{\sigma}^*$ by playing the game Φ, they play the non-cooperative game $G_{\sigma^*} \in \Psi$ where G_{σ^*} is the subgame at the second stage of the game Ω subsequent to $\boldsymbol{\sigma}^*$.*

In the long run, the aggregators $\mathcal{M}$ may change their behaviour with respect to selecting EV charging start times t_i. Therefore, to determine solutions for the game Φ, aggregators' empirical frequencies of choosing start times $t_i \in \mathcal{I}_i$ are considered under the notion of mixed strategies. In this scenario, the aggregators $\mathcal{M}$ face uncertainty in decision-making with their probabilistic choices of EV charging start times. Hence, in this chapter, the strategic behaviour of the aggregators $\mathcal{M}$ is studied under two user behavioural models: expected utility theory, i.e., the conventional game-theoretic approach, and prospect theory that learns the subjective non-ideal behaviour of users [Kahneman and Tversky, 1979].

7.5.1 Time Selection under Expected Utility Theory

To analyse the game Φ under mixed strategies, it is considered that each aggregator i evaluates the probability distribution over their strategy set $\mathcal{I}_i$ to maximise expected payoff. In classical game theory, expected utility theory is the main platform that is used to describe user behaviour and payoffs under the notion of mixed strategy. In this chapter, the expected payoff of each aggregator i under expected utility theory is given by

$$Q_{i,\Phi}^{\mathrm{EUT}}(\boldsymbol{y}) = \sum_{\boldsymbol{\sigma}\in\mathcal{I}} F_i(\boldsymbol{\sigma}) \prod_{j\in\mathcal{M}} y_j(t_j) \tag{7.14}$$

where $\boldsymbol{y} = (\boldsymbol{y}_i, \boldsymbol{y}_{-i}),\ \boldsymbol{y}_i = (y_i(1), y_i(2), \cdots, y_i(\tilde{t}_i)),\ y_i(t_i)$ is the probability that aggregator i selects time slot t_i as the EV charging start time, and $\boldsymbol{y}_{-i}$ is the probabilities of the other aggregators $i' \in \mathcal{M}\backslash i$ of choosing their EV charging start times.

Intuitively speaking, the payoff calculation under expected utility theory implies that players assess probabilities of their opponents' actions identical to their objective likelihoods. However, empirical evidence from sociology infers that this assumption may not be valid in many real world applications as often users, such as car park managers in our case study, underweight high probability events and overweight low probability events when they face risk and uncertainty [Kahneman and Tversky, 1979].

7.5.2 Time Selection under Prospect Theory

The intuition behind prospect theory is to describe user behaviour that cannot be understood by assuming rational choices of users as in normative expected utility theory [Kahneman and Tversky, 1979]. In the real world, it has been shown that people exhibit subjective behaviour rather than objective behaviour in payoff maximisation problems. This section investigates how the aggregators $\mathcal{M}$ maximise their utilities in the game Φ while subjectively evaluating their neighbours' behaviour.

Prospect theory uses weighting effects to characterise the subjective behaviour of users [Kahneman and Tversky, 1979] and in particular, probability weighting functions are widely investigated [Neilson and Stowe, 2002]. In general, a probability weighting function $w_i(y)$ indicates the subjective evaluation of aggregator i on an action played with probability y. In this chapter, Prelec's probability weighting function [Prelec, 1998] is used that is given by

$$w_i(y) = \exp(-(-\ln\, y)^{\kappa_i}) \tag{7.15}$$

where κ_i is a weighting parameter of aggregator i and $0 < \kappa_i \leq 1$. It is important to note that aggregator i becomes more subjective and deviates more from objective evaluation over probabilities as κ_i moves from 1 towards 0. On the other hand, $\kappa_i = 1$ implies that aggregator i perceives the action with probability y objectively, and therefore, their subjective evaluation and objective evaluation are identical.

Here, it is assumed that the subjective probabilities of aggregator i of their own actions are equal to the objective probabilities. Then the expected payoff of each aggregator i under prospect theory is given by

$$Q_{i,\Phi}^{\mathrm{PT}}(\boldsymbol{y}) = \sum_{\boldsymbol{\sigma}\in\mathcal{I}} F_i(\boldsymbol{\sigma}) y_i(t_i) \Bigg(\prod_{i'\in\mathcal{M}\backslash i} w_i(y_{i'}(t_{i'})) \Bigg). \tag{7.16}$$

7.5.3 ϵ-Nash equilibria

In this section, the solutions for the game Φ under expected utility theory and prospect theory are studied. In particular, ϵ-Nash equilibria for the game Φ are investigated under two models due to their attractive properties such as computational usefulness. Moreover, every Nash equilibrium is surrounded by ϵ-Nash equilibria for small $\epsilon > 0$ [Brown and Shoham, 2008]. A mixed strategy profile $\hat{\boldsymbol{y}} = (\hat{\boldsymbol{y}}_i, \hat{\boldsymbol{y}}_{-i})$ is an ϵ-Nash equilibrium for the game Φ if it satisfies

$$Q_{i,\Phi}(\hat{\boldsymbol{y}}_i, \hat{\boldsymbol{y}}_{-i}) \geq Q_{i,\Phi}(\boldsymbol{y}'_i, \hat{\boldsymbol{y}}_{-i}) - \epsilon, \ \forall \boldsymbol{y}'_i \in \mathcal{A}_i \backslash \hat{\boldsymbol{y}}_i, \ \forall i \in \mathcal{M} \tag{7.17}$$

where $\hat{\boldsymbol{y}}_{-i}$ is the equilibrium mixed strategy profile of the other aggregators $i' \in \mathcal{M}\backslash i$, $\mathcal{A}_i$ is the set of all possible mixed strategy profiles of aggregator i over $\mathcal{I}_i$, and $\epsilon > 0$. Note that, in (7.17), $Q_{i,\Phi}$ generalises $Q_{i,\Phi}^{\mathrm{EUT}}$ under expected utility theory and $Q_{i,\Phi}^{\mathrm{PT}}$ under prospect theory.

Remark 4. *Proposition 2 implies that finding a mixed strategy ϵ-Nash equilibrium of the game Φ under expected utility theory or prospect theory leads to a mixed strategy subgame perfect ϵ-Nash equilibrium [Flesch and Predtetchinski, 2015] of the game Ω.*

For the game Φ, under each user behavioural model, an ϵ-Nash equilibrium that is closely located to a mixed strategy Nash equilibrium is explored. To this end, the iterative algorithm proposed in [Wang et al., 2015b] is used where the algorithm was proven to converge to an ϵ-Nash equilibrium close to a mixed strategy Nash equilibrium of a finite non-cooperative game under both expected utility theory and prospect theory. In a nutshell, the algorithm is given by

$$\boldsymbol{y}_i^{(r+1)} = \boldsymbol{y}_i^{(r)} + \frac{\beta}{r+1}\big(\boldsymbol{z}_i^{(r)} - \boldsymbol{y}_i^{(r)}\big), \ 0 < \beta < 1 \tag{7.18}$$

where β is the inertia weight. Moreover, $\boldsymbol{z}_i^{(r)} = \big(z_i^{(r)}(t_{i,1}), \cdots, z_i^{(r)}(t_{i,\tilde{t}_i})\big)$ where

$$z_i^{(r)}(t_{i,t}) = \begin{cases} 1, \text{ if } t_{i,t} = \underset{t_i \in \mathcal{I}_i}{\text{argmax}} \; q_i(t_i, \boldsymbol{y}_{-i}^{(r-1)}), \\ 0, \text{ otherwise.} \end{cases} \tag{7.19}$$

Here, $q_i(t_i, \boldsymbol{y}_{-i}^{(r-1)})$ is the expected payoff of aggregator i when they select the pure strategy t_i for a given mixed strategy profile $\boldsymbol{y}_{-i}^{(r-1)}$ of their opponents $i' \in \mathcal{M}\backslash i$ at the iteration $r-1$. For prospect theory, $\boldsymbol{y}_{-i}^{(r-1)}$ considers the weighted probabilities of the aggregators $i' \in \mathcal{M}\backslash i$ at the iteration $r-1$. When the above algorithm converges, the ϵ-Nash equilibrium with regard to $\boldsymbol{y}$ is found under expected utility theory and prospect theory.

7.6 Simulation Results

7.6.1 Simulation Setup

To numerically examine the impacts of the EV charging competition among the EV aggregators with their ideal and non-ideal behaviour, a system with five EV aggregators ($N = 5$) is considered. Assuming a workplace EV charging scenario, the entire charging duration $\mathcal{T}$ spans from 8.00 AM to 4.00 PM and $M = 16$ with $\Delta t = 30$min.

It is assumed that the EV fleet at each aggregator i has 10 EVs and EV chargers at each aggregator i uses Level 2 charging. Level 2 charging is the primary approach used for EV charging at public places and typically uses EV charging rates between 3 kW and 20 kW [Yilmaz and Krein, 2013]. For simulations in this chapter, three types of EVs are considered, namely, Toyota Prius (3.8 kW, 4.4 kWh), Chevrolet Volt (3.8 kW, 16 kWh), and Nissan Leaf (3.3 kW, 24 kWh) [Yilmaz and Krein, 2013]. The distributions of different types of EVs at each aggregator i are given in Table 7.1. Initial percentage SOC levels of the EVs controlled by each aggregator i were randomly chosen between 0% and 100% of EVs' maximum energy storage capacities. It is assumed that all EVs should be charged to 100% of their maximum energy storage capacities by the time $\mathcal{T}$. The charging efficiency η_i of EV chargers controlled by each aggregator i is assumed to be 0.864 that is equivalent

Table 7.1: Number of different types of EVs available at each aggregator $i \in \mathcal{M}$

i	Toyota Prius	Chevrolet Volt	Nissan Leaf
1	2	3	5
2	2	5	3
3	3	2	5
4	3	5	2
5	5	3	2

to the average Level 2 charging efficiency given in [Forward et al., 2013]. Target energy demand profiles of each aggregator i were generated such that their target energy demand at time t is equal to the average of the total energy demand with respect to participating time information. For instance, if aggregator i starts charging their EVs at time slot $t_i \in \mathcal{I}_i$, then $\bar{x}_{i,t} = E_i/((M - t_i) + 1),\ t_i \leq t \leq M$. For each aggregator i, $g_{i,t}$ is randomly chosen from the set $\{10, 11, \cdots, 20\}$. Under these circumstances, Table 7.2 presents the possible EV charging start time strategy profiles $\mathcal{I}_i$ for the considered set of aggregators.

In simulations, $\boldsymbol{L}_b$ was assumed to be the aggregate energy demand of 200 residential facilities where the average energy demand profile between 8.00 AM and 4.00 PM is equivalent to the average energy demand profile of the Western Power Network in Australia between 8.00 AM and 4.00 PM in a Spring day [Jones et al., 2012]. For grid pricing, $\phi_t = 0.2$ AU cents/kWh^2 and $\delta_t = 0.2$ AU cents/kWh at each time $t \in \mathcal{T}$ so that the peak unit energy price of the grid when all EVs at each aggregator i are charged using their maximum charging power rates is equivalent to the peak usage domestic time-of-use tariff in [Origin, 2016].

For the algorithm in (7.18), initial probability distributions $\boldsymbol{y}_i^{(0)}$ were selected such that $\sum_{\mathcal{I}_i} y_i(t_i) = 1$ for each aggregator i, and $\beta = 0.7$. To compare results, an uncoordinated EV charging scenario was considered where all aggregators begin to charge their EV fleets from the time slot 1 using EVs' maximum charging power rates. The uncoordinated charging scenario uses the same energy cost models for the aggregators $\mathcal{M}$ in Section 7.2.

7.6.2 Results and Discussion

Fig. 7.1 shows the expected cost savings of each aggregator in $\mathcal{M}$ compared to the uncoordinated charging scenario under expected utility theory and prospect theory for two different $\kappa \in (0, 1]$ values ($\kappa = 0.1$ and $\kappa = 0.7$). Here, it is assumed that $\kappa_i = \kappa,\ \forall i \in \mathcal{M}$ where the probability weighting parameter κ is applied according to (7.15). It is important to note that when $\kappa = 0.1$ aggregators become more subjective and non-ideal than when

Table 7.2: EV charging start time strategy profiles $\mathcal{I}_i,\ \forall i \in \mathcal{M}$

i	EV Charging Start Time Strategy Profiles $\mathcal{I}_i$
1	$\{1, 2, \cdots, 5\}$
2	$\{1, 2, \cdots, 7\}$
3	$\{1, 2, \cdots, 10\}$
4	$\{1, 2, \cdots, 8\}$
5	$\{1, 2, \cdots, 11\}$

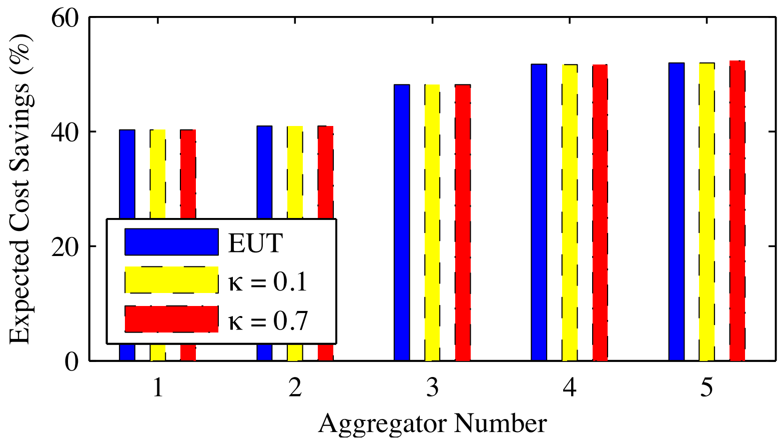

Fig. 7.1: Expected cost savings for the aggregators $\mathcal{M}$ under expected utility theory and prospect theory when $\kappa = 0.1$ and $\kappa = 0.7$.

$\kappa = 0.7$ because as κ tends to 0 from 1, aggregators deviate further from the objective behaviour assumed in expected utility theory. Table 7.3 presents the mixed strategy ϵ-Nash equilibria obtained for the game Φ under expected utility theory and prospect theory. According to the table, when aggregators have more subjective behaviour with $\kappa = 0.1$, the equilibrium probability distributions over $\mathcal{I}_i$ of each aggregator i deviate from that of expected utility theory. In particular, when $\kappa = 0.1$, the fourth and fifth aggregators prefer to participate from the time slot 1, whereas they prefer to participate from the time slot 3 under expected utility theory. When aggregators behave closer to the objective behaviour by adopting $\kappa = 0.7$, the fifth aggregator is more likely to start EV charging in the time slot 3 and the fourth aggregator prefers the time slot 1. Despite the changes in probabilistic choices of choosing an EV charging start time, Fig. 7.1 depicts that for each κ value in prospect-theoretic analysis, the expected cost savings for the aggregators $\mathcal{M}$ remain almost same as the savings obtained under expected utility theory ($\kappa = 1$).

Fig. 7.2 illustrates the aggregators' expected EV charging grid loads in the time slot 1 under prospect theory with $\kappa = 0.1$ and $\kappa = 0.7$ compared to that of expected utility theory. Fig. 7.3 shows the temporal variation of the expected aggregate grid load after studying the EV charging competition under expected utility theory and prospect theory when $\kappa = 0.1$. Fig. 7.2 shows that when $\kappa = 0.1$, the fifth aggregator incurs a significant EV charging load on the grid in the time slot 1 compared to their expected EV charging grid loads in expected utility theory and in prospect theory with $\kappa = 0.7$. Similarly, when $\kappa = 0.1$, the fourth aggregator also has a significant charging load in the time slot 1 compared to expected utility theory. Similar trends were observed for the time slot 2 as well. This is because both aggregators prefer to participate from the time slot 1 when $\kappa = 0.1$, whereas, in expected utility theory, they prefer to participate from the time slot 3 (see Table 7.3). As shown in Fig. 7.3, the increase in EV charging loads of the fourth and

Table 7.3: Percentage participation probabilities of the aggregators $i \in \mathcal{M}$ for $t_i \in \mathcal{I}_i$ under expected utility theory (EUT) and prospect theory (PT) when $\kappa = 0.7,\ 0.1$

	EUT probabilities i.e., when $\kappa = 1$ (%)					PT probabilities when $\kappa = 0.7$ (%)					PT probabilities when $\kappa = 0.1$ (%)				
t_i	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$
1	99.75	99.75	99.04	4.48	1.59	99.81	99.81	99.81	99.81	6.31	99.12	99.12	99.12	99.12	99.12
2	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03	0.02	0.02	0.1	0.1	0.08	0.1	0.1
3	0.03	0.03	0.73	95.31	98.18	0.02	0.02	0.02	0.02	93.52	0.1	0.1	0.1	0.1	0.05
4	0.03	0.04	0.02	0.03	0.01	0.02	0.02	0.02	0.02	0.01	0.1	0.08	0.1	0.1	0.03
5	0.16	0.05	0.03	0.03	0.01	0.13	0.04	0.02	0.02	0.02	0.58	0.2	0.1	0.1	0.1
6	-	0.05	0.03	0.01	0.03	-	0.04	0.02	0.02	0.02	-	0.2	0.1	0.1	0.1
7	-	0.05	0.03	0.03	0.03	-	0.05	0.02	0.02	0.02	-	0.2	0.1	0.1	0.1
8	-	-	0.03	0.08	0.03	-	-	0.02	0.07	0.02	-	-	0.1	0.28	0.1
9	-	-	0.03	-	0.03	-	-	0.02	-	0.02	-	-	0.1	-	0.1
10	-	-	0.03	-	0.03	-	-	0.02	-	0.02	-	-	0.1	-	0.1
11	-	-	-	-	0.03	-	-	-	-	0.02	-	-	-	-	0.1

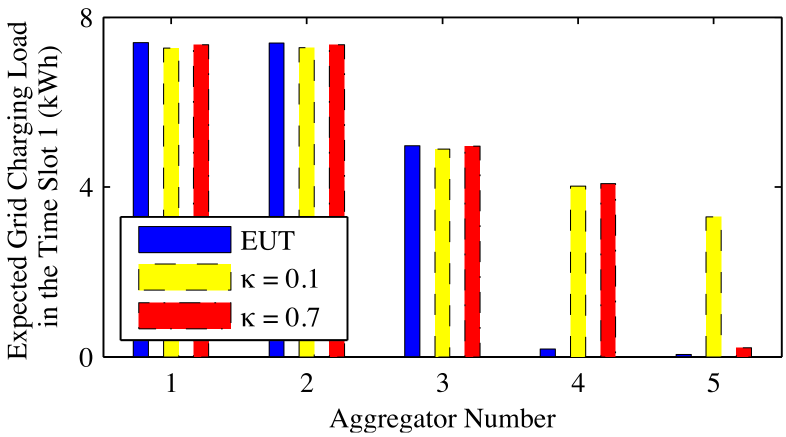

Fig. 7.2: Expected EV charging loads on the grid in the time slot 1 of the aggregators $\mathcal{M}$ under expected utility theory and prospect theory when $\kappa = 0.1$ and $\kappa = 0.7$.

fifth aggregators when $\kappa = 0.1$ results in nearly 9% higher load on the grid in each time slot (time slot 1 and 2) than expected utility theory.

Next, the influences of EV charging competition among the EV aggregators were studied across a range of possible κ values. Here, κ was varied in the range $(0, 1]$. Fig. 7.4 illustrates the average expected cost savings of the aggregators $\mathcal{M}$ compared to the uncoordinated charging scenario with respect to changes in κ. Fig. 7.5 depicts the variations of expected peak-to-average ratio reductions compared to the uncoordinated charging scenario with varying κ. From the grid's perspective, a higher peak-to-average

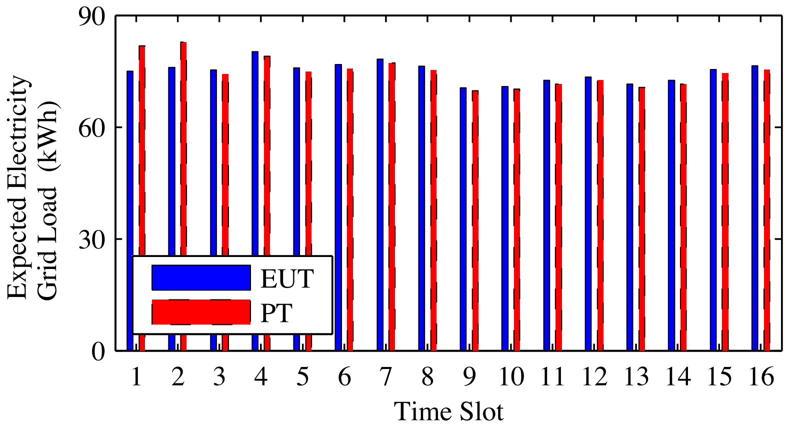

Fig. 7.3: Temporal variation of expected aggregate grid load under expected utility theory and prospect theory when $\kappa = 0.1$.

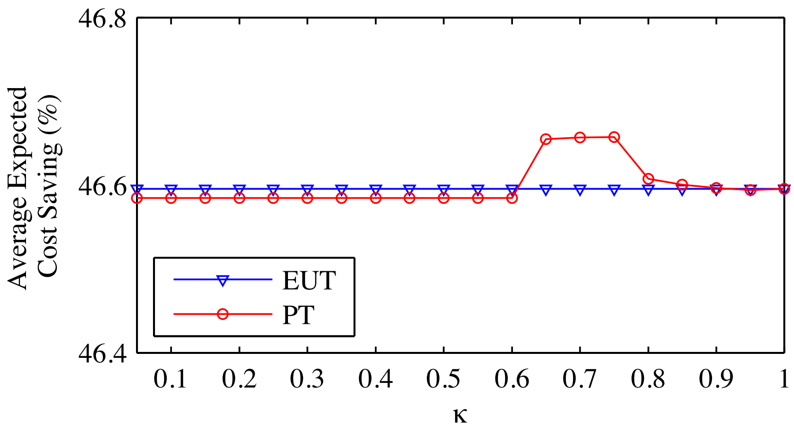

Fig. 7.4: Average of expected cost savings of the aggregators $\mathcal{M}$ with different κ.

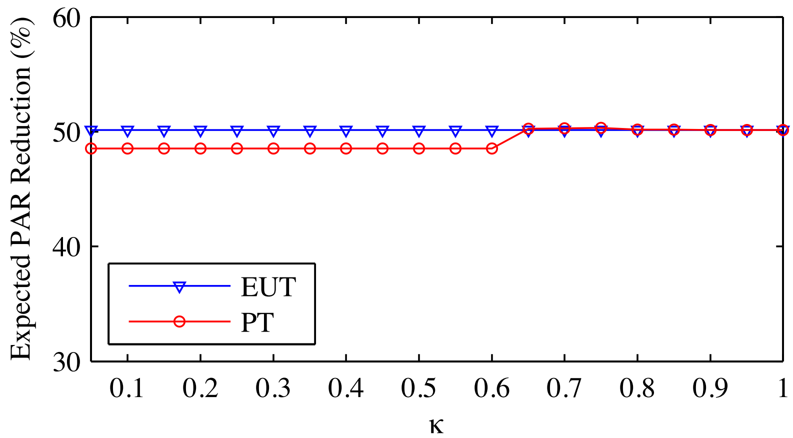

Fig. 7.5: Expected peak-to-average ratio (PAR) reduction with different κ.

ratio reduction is preferred because it implies better peak load regulation compared to the uncoordinated EV charging case. According to Fig. 7.4, when $0 \leq \kappa \leq 0.6$, the average expected cost savings of the aggregators $\mathcal{M}$ are slightly lower than that obtained under expected utility theory. In particular, compared to the average expected cost saving under expected utility theory, this reduction is insignificant with only 0.01%. When $0.65 \leq \kappa \leq 0.75$, each aggregator in $\mathcal{M}$ receives a higher average expected cost saving with nearly 0.1% increase. On the other hand, Fig. 7.5 shows that the expected peak-to-average ratio reductions remain nearly unchanged across the range of κ. When $0 \leq \kappa \leq 0.6$, the peak-to-average ratio reductions are slightly lower than those achieved under expected utility theory. This is because, in this range of κ, the EV charging competition among the aggregators leads to higher peak loads on the grid than the peak grid load under expected utility theory, for example, as shown in Fig. 7.3.

Finally, the impacts of the EV charging competition when each aggregator i has different κ values, i.e., $\kappa_i = \kappa_j$ for $\{i.j\} \in \mathcal{M}$, $i \neq j$, were investigated. To this end, it was considered $\boldsymbol{\kappa} = (0.7,\ 0.5,\ 0.9,\ 0.1,\ 0.3)$ as the matrix of κ_i of the aggregators $\mathcal{M}$ under prospect theory. All other parameters are as specified for the previous simulation. Fig. 7.6 shows the expected cost savings for each aggregator in $\mathcal{M}$ compared to the uncoordinated EV charging scenario under expected utility theory and prospect theory. Similar to the case where $\kappa_i = \kappa$, $\forall i \in \mathcal{M}$, here the prospect-theoretic energy cost savings remain nearly the same as expected cost savings under expected utility theory. On the other hand, the expected peak-to-average reduction of 50.16% under expected utility theory increases slightly to 50.30% reduction in the prospect-theoretic scenario with $\boldsymbol{\kappa} = (0.7,\ 0.5,\ 0.9,\ 0.1,\ 0,3)$.

7.7 Concluding Remarks

This chapter investigated impacts of non-ideal, subjective participating behaviour of multiple electric vehicle (EV) aggregators, which might be run by car park managers, interacting in a coordinated EV charging competition. In the presented EV charging

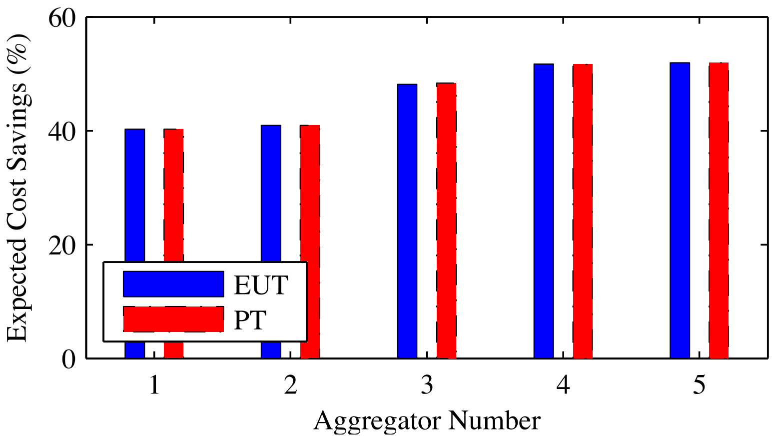

Fig. 7.6: Comparison of the expected cost savings of the aggregators $\mathcal{M}$ under expected utility theory and prospect theory when $\boldsymbol{\kappa} = (0.7,\ 0.5,\ 0.9,\ 0.1,\ 0,3)$.

strategy, each aggregator minimises their individual EV charging costs by selecting optimal EV charging start times and energy profiles. The EV charging competition among the aggregators was modelled by developing a two-stage non-cooperative game among the aggregators, which was studied under prospect theory to incorporate non-ideal participating actions of the aggregators. The two-stage non-cooperative EV charging game can obtain a subgame perfect ϵ-Nash equilibrium when the game is played with either ideal, or non-ideal, participating actions of the aggregators. Through numerical simulations, we have shown that the benefits of the coordinated EV charging strategy, in terms of EV charging energy cost reductions and peak load regulation, are significantly resilient to non-ideal participating actions taken by the aggregators.

Chapter 8

Conclusions and Future Work

In this chapter, we summarise the works that have been developed in the previous chapters while presenting their research contributions. Then, we discuss the potential future extensions of the thesis.

8.1 Conclusions

This thesis primarily focused on introducing novel energy trading systems for decentralised demand-side management with the use of a small-scale community energy storage (CES) device and household-distributed photovoltaic (PV) energy generation. Based on the proposed energy trading systems, the thesis presented how the individual participants can be benefited through decentralised energy trading while delivering load regulation to the power grid.

The first problem that we investigated is how to implement decentralised energy trading strategies among residential users with PV energy so that the users are motivated to trade surplus PV energy with a CES device that can be dispatched later to supply peak energy demand. To answer this problem, we introduced a novel energy trading system between a CES device and users by taking into account users' autonomy to minimise personal energy costs. A non-cooperative repeated game was developed to investigate self-interested interactions of users who trade locally generated PV energy with the CES device. The convergence of the non-cooperative game to a Pareto-optimal Nash equilibrium was proven. Our findings demonstrated that the equilibrium energy trading strategies of participating users in the system lead to a significant load reduction on the grid while delivering reduced energy costs for the users. It was shown that the proposed energy trading system can be further benefited by an increasing fraction of participating users.

The second problem we studied in the thesis is how the CES operator can be benefited through facilitating energy trading strategies of self-seeking users. To answer this problem, we developed a bi-level energy trading system between the CES operator and the users based on a non-cooperative Stackelberg game. The non-cooperative energy trading between the competitive CES operator and the users achieves a Stackelberg equilibrium that is optimal for both entities. Compared to two other potential CES operator models, i.e., a centralised cooperative CES operator model and a benevolent CES operator model, it was shown that the proposed competitive energy trading system can provide the best trade-off of operating environment between the CES operator and the participating users.

Effective day-ahead demand-side management that produces load management strategies a day in advance requires accurate energy consumption and energy generation forecasts. The proposed energy trading systems between the CES operator and PV energy users in Chapter 3 and Chapter 4 primarily focused on day-ahead demand-side management that utilises energy demand and PV energy forecasts. To investigate the performance of the energy trading systems with imperfect information that arises with inaccurate PV energy and users' demand forecasts, we introduced forecast errors into the user demand and PV energy generation profiles so that the games among the players are played with imperfect information. Our findings based on numerical performance analyses showed that the benefits of the proposed energy trading systems are robust to imperfect energy forecast information.

A natural question that arises in multiuser settings such as consumer-centric demand-side management is their sensitivity to potential non-ideal user behaviour that cannot be apprehended by assuming completely rational behaviour of users. By extending the competitive Stackelberg game-theoretic energy trading system so that the users can choose energy trading start times, we answered this question with the use of prospect theory. In particular, following a non-cooperative game among the users, we investigated users' non-ideal energy trading start time selection that may occur as a consequence of their subjective views on opponents' actions. The study showed that, with time varying subsets of active participating users, the energy trading system can attain a unique Stackelberg equilibrium between the energy trading strategies of the CES operator and the users. Furthermore, the results from a numerical case study showed that the proposed energy trading system is robust to non-ideal participating time selection of the users.

Motivated by the study of non-ideal user behaviour in a bi-level energy trading system between a CES device and PV energy users, finally, we applied the insights of prospect theory to investigate impacts of potential non-ideal actions of EV aggregators competing in a coordinated EV charging system. In the thesis, the coordinated EV charging competition among the aggregators was modelled as a two-stage non-cooperative game among the aggregators. We showed that the competitive EV charging strategies of the aggregators lead to a subgame perfect ϵ-Nash equilibrium even when the aggregators' actions are non-ideal. Furthermore, numerical performance analysis demonstrated that the benefits of the coordinated EV charging strategy presented in the thesis, in terms of peak-to-average ratio reductions and EV charging cost reductions, are resilient to non-ideal actions adopted by the aggregators.

8.2 Future Work

The discussed energy management frameworks has numerous potential extensions. This section dicusses important expansions to the research works presented in this thesis.

8.2.1 Energy Trading with Incomplete Information

In the energy trading systems in Chapter 3 and Chapter 4, we developed non-cooperative repeated games among the participating users. To achieve preliminary analysis, in those settings, we assumed that the actual total energy consumption of other users are made available to each user by a central controller to determine users' energy trading strategies. This assumption is also valid for the analysis in Chapter 5 where we investigated the performance of the game-theoretic energy trading systems with imperfect information. Overall, in these settings, the information about the games were considered to be common knowledge among the players.

According to our energy cost models, personal energy costs of the participating users depend on the total energy consumption of the other users, which relies on fluctuating PV power generation and demand profiles. In the real world, due to the uncertainty of PV energy and demand profiles, the actual total energy consumption of other users might be unknown information to each other as this information directly depends on local PV energy generation and demand profiles. Therefore, users have to strategically reason about their energy trading strategies based upon uncertain estimates of the total energy consumption of other users made by the central controller. This would create uncertainties among users about each others' payoffs and hence, about the game. Such situation reflects that the non-cooperative games among the users are played with incomplete information [Brown and Shoham, 2008]. In this paradigm, the repeated games among the participating users in Chapter 3 and in Chapter 4 can be extended to non-cooperative repeated games where each stage game is played with incomplete information. Mathematical tools from Bayesian game theory [Brown and Shoham, 2008] can be used to model how the participating users anticipate their opponents' energy trading strategies based on uncertain information about PV energy and user demand profiles.

8.2.2 Cooperative Energy Exchange between Multiple Hierarchical Energy Trading Systems

In addition to non-cooperative game theory, cooperative (or coalitional) game theory [Brown and Shoham, 2008] provides advanced mathematical tools to investigate how smart grid nodes can cooperate to improve system-wide objectives of the electricity grid [Saad et al., 2012]. For example, cooperative game-theoretic frameworks have been used to investigate energy exchange among geographically dispersed microgrids to reduce power distribution losses [Saad et al., 2011]. Having insights from these works, it would be interesting to investigate cooperative energy exchange among multiple energy trading systems similar to our Stackelberg energy trading setting where one system with net surplus PV energy can trade energy to another system with net energy deficit rather than directly selling energy to the grid. Such frameworks would enhance demand-side management as users in the energy trading systems can consume energy traded by nearby systems without relying on the main power grid. This would result in better utilisation of CES energy storage devices dispersed across a vast geographic range for effective demand-side management.

8.2.3 Community Energy Trading with Consumer-owned Photovoltaic Energy Generation and Energy Storage Devices

With the advancements of battery energy storage applications at residential level such as EVs, users might store some of their locally produced energy for future energy use. As a prospective extension to the energy trading scenarios in this thesis, the energy trading systems could be studied as tri-level settings by considering that the participating users own energy storage devices connected to their rooftop PV panels. In particular, pricing mechanisms that would encourage PV energy users to sell some of their surplus PV energy to the CES device while storing PV energy in their local energy storage devices should be identified so that the stored energy in the CES device can be dispatched to compensate peak energy demand of the overall community. Similar non-cooperative game-theoretic frameworks can be used to study the non-cooperative interactions among the participants when they select their optimal energy trading strategies.

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