Energy Management System for the Integration of Electric Vehicles in the Smart Grid

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Preface

This thesis has been prepared at School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, New Zealand in fulfilment of the requirements for the award of a degree of Doctor of Philosophy (PhD). The work has been carried out in the period from February 2019 to October 2023 under the supervision of Dr. Ramon Zamora and Prof. Tek Tjing Lie. The thesis aimed at developing transactive energy management frameworks for integrating electric vehicles with PV-based distribution network. The research involves a comprehensive development of transactive energy trading models, considering factors such as feasibility, advantages, and challenges, with a specific emphasis on their suitability within the context of workplace PV-integrated electric vehicles. While minimizing operational costs, the design of the transactive energy management system considers the prominent issue of range anxiety, which stands as a significant barrier to the adoption of electric vehicles (EVs). The work carried out in the thesis was presented in the form of manuscripts. The link between the work presented in each manuscript and its relevance to the main idea of the thesis was explicitly mentioned at the beginning of each chapter. Furthermore, each chapter was dedicated to describing the work presented in the manuscripts.

Abstract

Amid the global pursuit of sustainability, Electric Vehicles (EVs) and solar energy source (PV) have emerged as transformative technologies with the potential to revolutionize the transportation and energy sectors. EVs promise to reduce greenhouse gas emissions and decrease the reliance on fossil fuels. EVs act as mobile energy storage devices with significant capacity. When connected to the grid, they can absorb excess electricity during periods of high renewable energy generation and release it during peak demand, effectively acting as grid batteries. Meanwhile, PV systems offer a clean and renewable energy source that can be harnessed at the point of generation, reducing stress on the grid, and promoting energy independence. However, the seamless integration of these technologies into the existing electricity grid presents multifaceted challenges that must be addressed to fully unlock their potential.

This thesis delves into the dynamic relationship between PV systems and EVs, with a specific focus on transactive energy management as a pivotal means to optimize their interaction with the distribution networks. EVs, predominantly in a parked state, present an untapped opportunity for active engagement in transactive markets, enabling the sale of surplus energy to the grid during periods of favourable pricing, thereby affording novel revenue streams to EV owners. The central goal of this research is to develop frameworks that enable the efficient exchange of energy between PV-integrated distribution networks and EVs while considering technical, social and economic aspects.

One of the core challenges lies in the technical integration of PV-EV systems with the distribution networks. This encompasses optimizing EV charging schedules, managing bidirectional power flows, accounting for system uncertainties and accurate forecasting strategies. The objective is to optimize the utilization of PV for EV charging and maximize the active involvement of EVs in transactive energy markets, thereby increasing the reliability and stability of the distribution network.

Moreover, the thesis explores various transactive models that facilitate energy exchange, such as peer-to-peer energy trading and aggregator-based markets. The models are evaluated in terms of feasibility, benefits, and challenges, with a particular focus on their applicability in the context of workplace PV-integrated EVs.

To optimize energy transactions, the thesis develops advanced algorithms that leverage real data including PV generation patterns, EV charging behaviour, electricity prices, and market dynamics. These algorithms are designed to minimize costs while considering system uncertainties to ultimately promote more efficient energy usage.

The thesis substantiates its findings through real-world case studies and simulations. Range anxiety, being the biggest barrier to the adoption of EVs, is considered in designing the transactive energy management system while minimizing operational costs.

In conclusion, this research underscores the critical importance of transactive energy management for PV-integrated workplace electric vehicles. By addressing the complex technical, economic, and operational challenges, this work contributes to the broader efforts aimed at harnessing the full potential of EV-based transactive energy markets and advancing the global energy transition. The proposed methods in this research are generic, theoretically flexible, and capable of being applied to the distribution networks to smartly manage EVs' participation in transactive energy markets.

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Attestation of Authorship

I hereby declare that this submission is my own work and that the work presented in this thesis is solely based on my own research. The content of this PhD work is original, except where the work is referenced. I also declare that this work has not been submitted in whole or in part for the purpose of degree or qualification at any degree-awarding institute. I declare that this thesis is my own work and contains nothing as an outcome of work done in internal and/or external collaboration.

………………………

Asaad Mohammad

October 2023

Co-Authored Works

Chapter title	Author	Contribution (%)
Chapter 2: Integration of Electric Vehicles in the Distribution Network: A Review of PV Based Electric Vehicle Modelling	A. Mohammad	85
	R. Zamora	10
	T. T. Lie	5
Chapter 3: Energy Management for EV Participation in Local Energy Markets	A. Mohammad	85
	R. Zamora	10
	T. T. Lie	5
Chapter 4: Transactive Energy Management of PV-Based EV Integrated Parking Lots	A. Mohammad	85
	R. Zamora	10
	T. T. Lie	5
Chapter 5: Transactive Energy Management of Solar-Based Range Anxious Electric Vehicle Integrated Parking Lots	A. Mohammad	85
	R. Zamora	10
	T. T. Lie	5

We, the undersigned, hereby agree to the percentages of participation to the chapters identified above:

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Dr. Ramon Zamora   Prof. Tek Tjing Lie
(Primary supervisor)   (Secondary supervisor)

Publications During the PhD Programme

A. Mohammad, R. Zamora, and T. T. Lie, "Integration of Electric Vehicles in the Distribution Network: A Review of PV Based Electric Vehicle Modelling," Energies, vol. 13, no. 17, p. 4541, Sep. 2020, doi: 10.3390/en13174541. **(Published)**

A. Mohammad, R. Zamora and T. T. Lie, "Transactive Energy Management of PV-Based EV Integrated Parking Lots," in IEEE Systems Journal, vol. 15, no. 4, pp. 5674-5682, Dec. 2021, doi: 10.1109/JSYST.2020.3043327. **(Published)**

A. Mohammad, R. Zamora and T. T. Lie, "Energy Management for EV Participation In Local Energy Markets," 2022 IEEE Transportation Electrification Conference & Expo (ITEC), Anaheim, CA, USA, 2022, pp. 1327-1331, doi: 10.1109/ITEC53557.2022.9813748. **(Published)**

A. Mohammad, R. Zamora and T. T. Lie, "Transactive Energy Management of Solar-Based Range Anxious Electric Vehicle Integrated Parking Lots," in Sustainable Energy, Grids and Networks, vol 38, pp. 101360, June 2024 **(Published**)

Acknowledgement

Chapter 1: Introduction

1. Background

Electric vehicles (EVs) are a type of transportation that uses electricity as their primary power source, instead of gasoline or diesel. They have gained popularity in recent years due to their environmental benefits, as they produce zero tailpipe emissions and are, therefore, much cleaner than gasoline-powered vehicles. In addition to their environmental advantages, EVs also have the potential to reduce our dependence on fossil fuels, as electricity can be generated from various sources, including renewable energy sources such as solar and wind power. This is particularly important as the world looks to transition away from fossil fuels and towards more sustainable energy sources. With transportation as one of the most significant contributors to GHG emissions, accounting for 39% of total domestic CO_2 emissions from the energy sector in NZ in 2019 [1], it is paramount to investigate sustainable means of transportation for NZ like EVs.

Beyond environmental benefits, EVs bring about a quieter and more peaceful urban environment by reducing noise pollution. They also promote energy independence by reducing dependence on imported oil and enhancing energy security. The instantaneous torque provided by electric motors offers a thrilling driving experience with quick acceleration, and regenerative braking systems further enhance energy efficiency. Additionally, electric vehicles often feature innovative technologies such as remote monitoring, over-the-air updates, and autonomous driving capabilities.

Another advantage of EVs is their economic benefits. Although the upfront cost of an EV may be higher than that of a gasoline-powered vehicle, the cost of owning an EV is often lower in the long run. This is because EVs have significantly lower operating costs due to factors such as lower fuel costs (electricity is typically cheaper than gasoline) and lower maintenance costs (EVs have fewer moving parts, which means they require less maintenance). As a result, many people who switch to EVs save money over time.

One significant advantage of EVs is the potential to act as an energy storage system through Vehicle-to-Grid (V2G) technology. Although a single EV has a minuscule battery capacity but when multiple EVs are aggregated together, they can provide grid support in the form of backup power, ancillary services, frequency and voltage support, storage for renewable energy sources etc. If EV charging is done intelligently to match the load demand pattern with the renewable energy generation pattern, better utilisation of base-load capacity can be achieved. Fig 1 shows a pictorial view of an EV charging system connected to the grid.
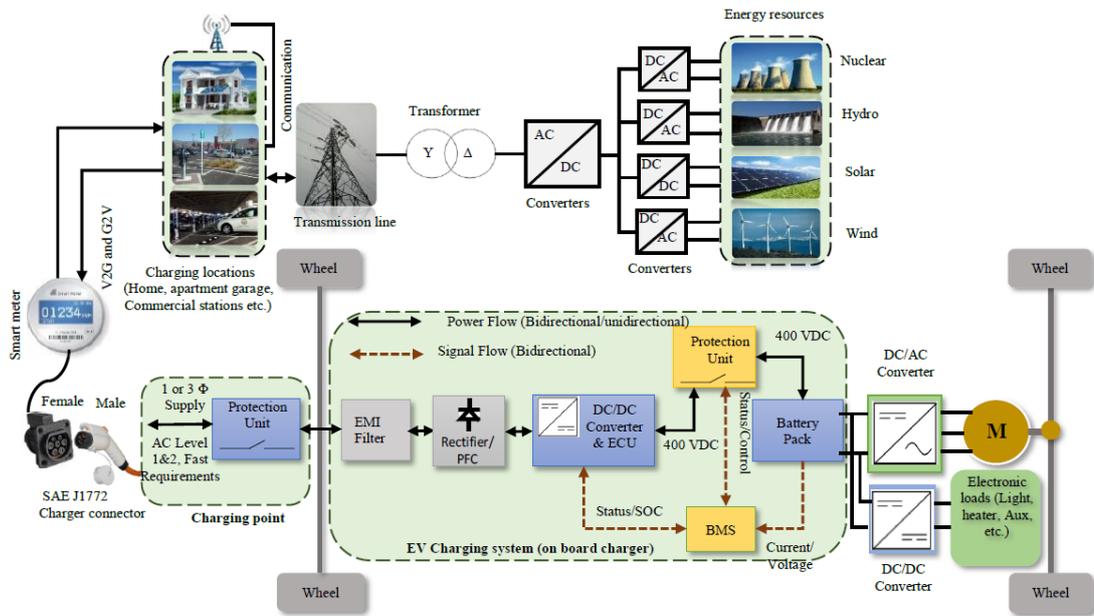
Fig 1: Grid-connected EV charging system [2]

One of the key challenges limiting the widespread adoption of electric vehicles (EVs) is the issue of charging infrastructure. While significant progress has been made in expanding charging networks, there remains a need for further development and accessibility, especially in rural and less densely populated areas. Range anxiety, the fear of running out of battery charge before reaching a charging station, is a legitimate concern for potential EV buyers, and addressing it is crucial to encourage mass adoption. Additionally, charging times, particularly for fast-charging stations, need to be further reduced to match the convenience of refuelling a gasoline vehicle. Moreover, standardization and interoperability across charging networks are essential to provide a seamless experience for EV owners. Addressing these infrastructure challenges is a pivotal step in making electric vehicles more convenient, practical, and appealing to a broader range of consumers, ultimately accelerating their adoption and contributing to a sustainable transportation future. While the number of EV charging stations is increasing, they are still not as widely available as gasoline stations. However, the charging infrastructure will likely improve as the demand for EVs grows.

2. New Zealand EV composition

The current market share of EVs in New Zealand is 1.77% of the total light vehicle fleet (end of May 2023), as depicted in Fig 2 [3]. While EVs are a minuscule share of the entire vehicle fleet, they are slowly increasing in numbers.
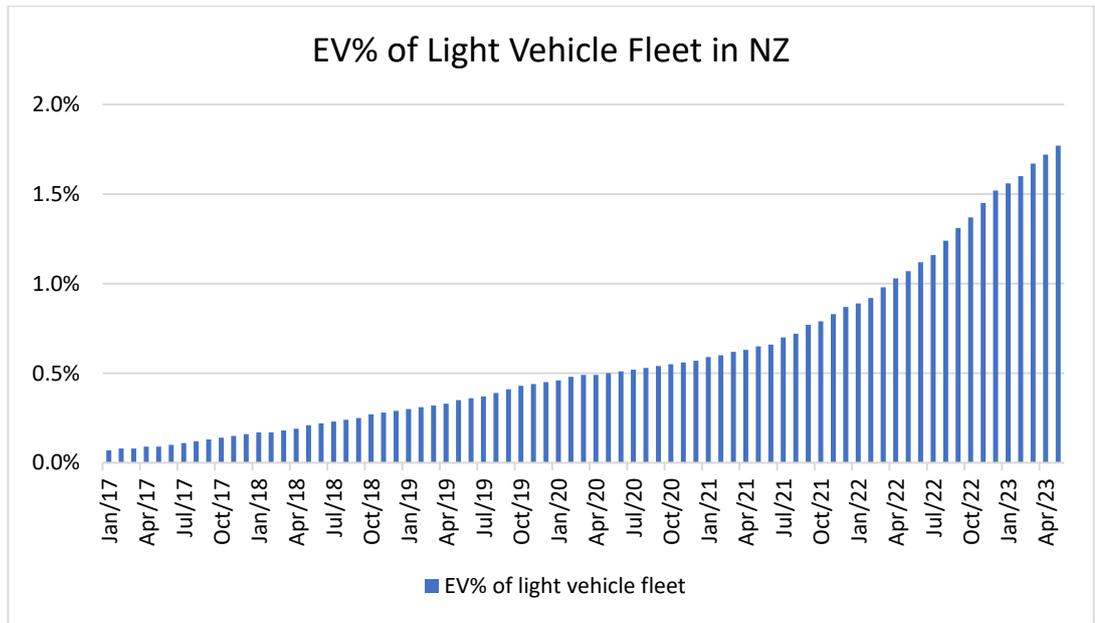
Fig 2: NZ market share of EVs in light vehicle fleet

Fig 3 shows the percent-wise yearly sale of new light vehicles by fuel type in NZ [4]. It can be observed that while the sales of gasoline vehicles are decreasing, hybrid and pure EVs are on the rise. This rapid rise of hybrid and pure EVs has been primarily linked to the Clean Car Discount [5], which started in July 2021. With the high upfront cost being the most significant barrier to EV adoption, this incentive from the NZ government effectively reduced the price. The Clean Car Discount boosted the EV adoption rate, and the market share is estimated to rise to 75% of the new car sold by the end of 2025 [6].
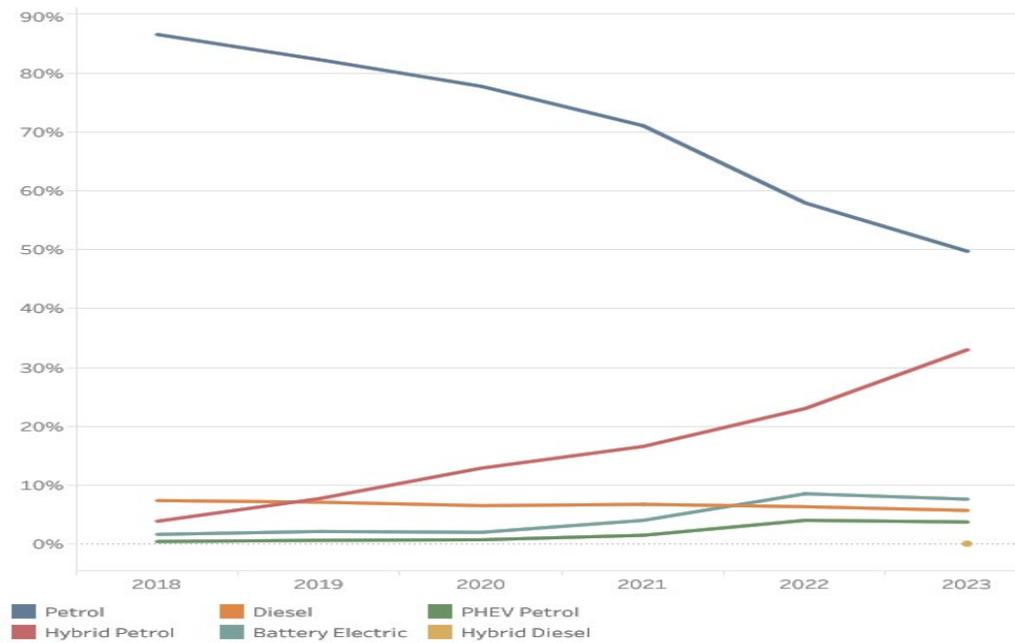
Fig 3: NZ yearly light vehicle registrations share

The electric fleet composition in Fig 4 shows the consumers' preference for car manufacturers [4]. Japanese-manufactured EVs enjoy a predominant market share of more than 70% of all EV

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registration in NZ. Currently, hybrid EVs from Toyota are the most popular electric cars in NZ. In the Battery Electric Vehicle (BEV) category, Nissan's Leaf and Tesla are the most common electric vehicles.
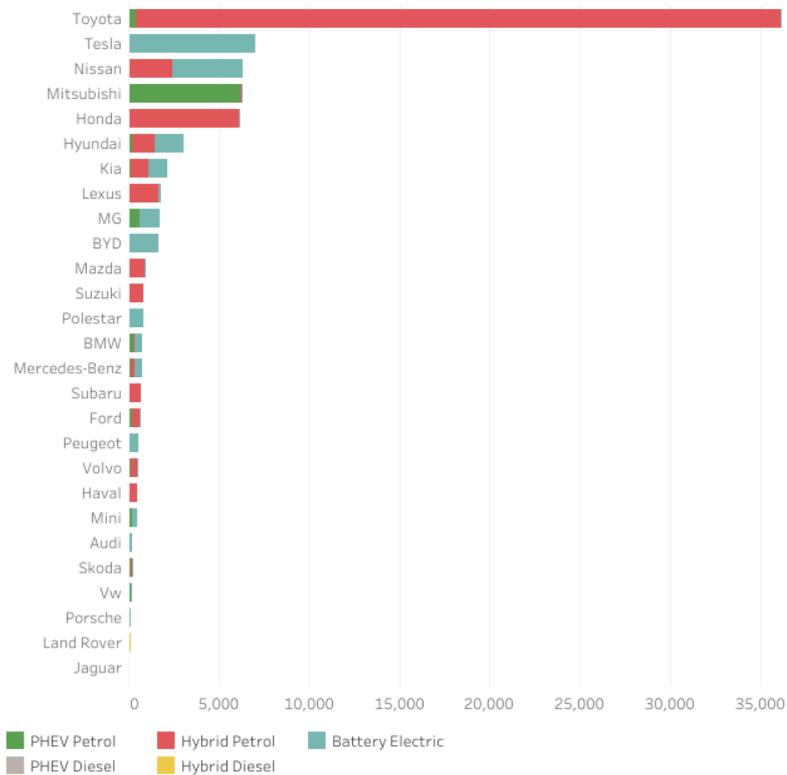
Fig 4: NZ light EV fleet composition

While EVs are witnessing tremendous growth in adoption, they still constitute a small percentage of the total vehicle fleet due to factors such as high cost, range anxiety, and inadequate charging infrastructure [7]. However, with the government mandate to electrify the transportation fleet by 2030, investments in charging infrastructure, and rising concerns over emissions and oil dependency, the EVs' total market share is poised to grow more rapidly in future.

3. EV Charging System

The EV charging system varies from slow home-based to ultrafast highway charging systems. Based on the power transfer mode, EV charging can be classified into conductive and inductive charging systems. The conductive charging system comprises a wired connection between the vehicle and the charger. It is further differentiated into an onboard or offboard system based on whether most of the charging components are present in the car (onboard system) or the charger (offboard system). The weight and size constraints of the onboard charging system only allow a slow rate of EV charging, thereby leading to developments in offboard charging systems for commercial purposes.

The conductive charging system can be divided into three levels based on power ratings: Levels 1, 2 and 3. Level 1 & 2 charging systems are called slow AC charging, whereas level 3 is fast DC charging. Further information on these levels is highlighted in Table 1. These levels are standard in North America and are defined by the SAE J1772 standard [8].

Table 1: Charging levels characteristics

	Level 1	Level 2	Level 3
Duration	10 – 16 hrs	2 – 6 hrs	20 – 40 mins
Power Ratings	1.4 kW (120V, 12A), 1.9 kW (120V, 16A)	19.2 kW (240V, 80A), 36 kW (240V, 150A)	96 kW (480V, 200A), 160 kW (400V, 400A)
Range/hr	4 – 11 km	20 – 80 km	200+ km
User case	Home-based night charging	Commercial charging (like work, shopping malls), home-based fast charging	Dedicated charging stations, highway chargers

Modes 1- 4 (defined in the IEC61851 standard [9]) are generally used instead of charging levels in Europe and China. Both are virtually the same, with additional grounding and control requirements in Europe, as shown in Fig 5 [10].
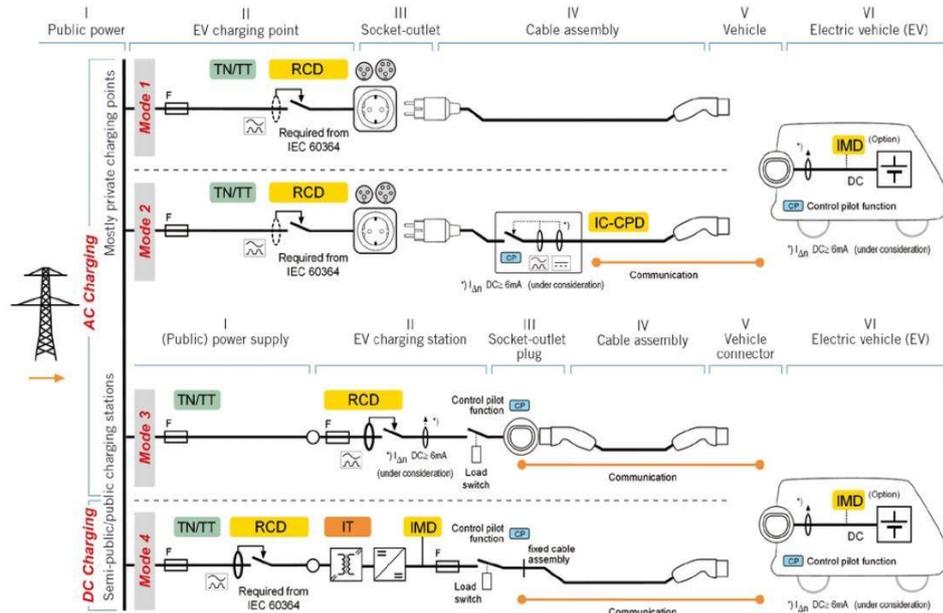
Fig 5: EV charging modes[10]

The inductive (or wireless) charging system works on the principle of electromagnetic energy transfer between receivers placed in EVs and transmitters in chargers without any physical connection. The inductive charging system can be static with stationary EVs or dynamic with EVs in motion.

4. Energy Market and EV

The concept of participation of EVs in the energy market was introduced in [11], with modelling and investigative analysis carried out in [12], [13]. As a single EV on its own is minuscule in terms of energy offered in the market, an aggregator entity of multiple EVs can be integrated into the markets. A large number of individual EVs participating in the energy market will also lead to high-volume transaction management costs and complexity. As the EV battery energy is readily available to dispatch, EVs can also be integrated into real-time energy markets or for ancillary service markets (regulation service market, reserve service market, capacity service market) rather than only day-ahead energy markets. Fig 6 shows the operating process of EV participating in the energy markets. The day-ahead energy market schedules energy transactions for the next day. The real-time energy market accounts for the energy imbalances between supply and demand in real-time.
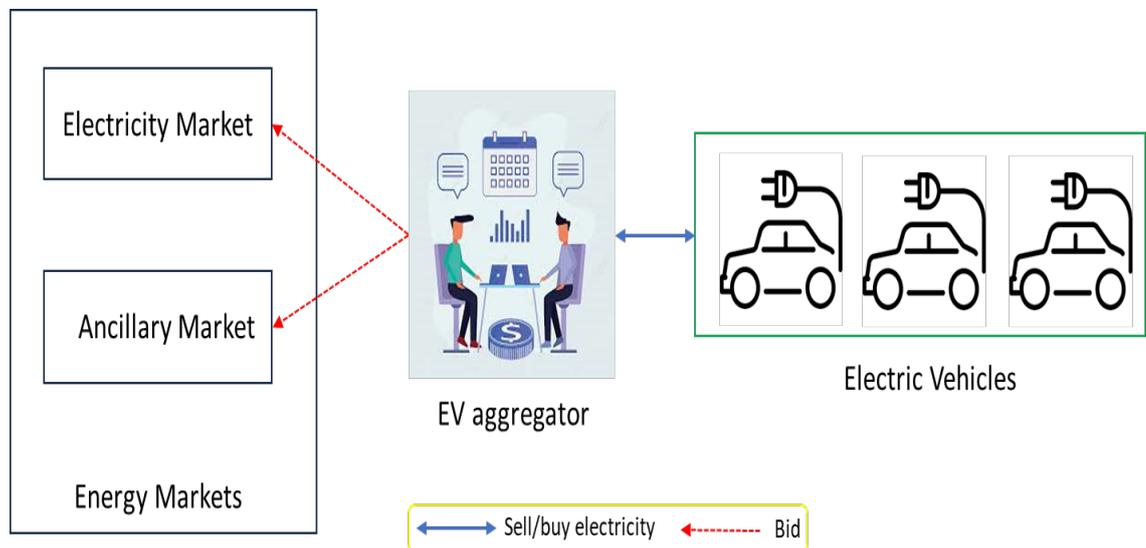
Fig 6: EV participating in the energy market

The aggregator agent offers financial incentives to EV users to partake in energy arbitrage and to compensate for battery degradation due to frequent charging-discharging cycles. In literature, the relationship between aggregator and EV users is generally modelled two ways: aggregator controlling the EV charging/discharging (centralised control) [14], [15] or EV users responding to aggregator signal as per availability/convenience (decentralised control) [16], [17]. The centralised control offers less flexibility but requires a less complex algorithm. In contrast, decentralised control provides more flexibility and requires a complex algorithm. The advantages and disadvantages of both approaches are explained in Chapter 2 of the thesis.

EV aggregators' involvement in the energy market means the need for the best scheduling while utilising these battery and renewable energy resources. Due to today's liberalised power markets, EV aggregators are eager to insure against the risk of daily price instabilities and uncertain

renewable generation as they are exposed to increasingly variable electricity prices. For aggregators to maximise their profit, forecasting the price of the electricity market and renewable energy generation is crucial. Ref [18] studies the economic impact of inaccurate forecasting on system operations from the supply-side perspective. To reduce the risk of high operating costs and hedge against the volatility in electricity prices, renewable energy generation, EV availability etc., various sources of uncertainty need to be modelled in the energy management system.

5. Transactive Energy Markets

The existing energy markets need reforms to balance the limited dispatchable energy sources and the increasing demand [19]. New market and balancing mechanisms are required to avoid high grid reinforcement costs and to adapt to the variations in load behaviour and volume.

Transactive energy markets (or local energy markets) have become an essential strategy for encouraging the integration of more distributed energy resources into the electrical grid [19]. Local Energy Markets (LEMs) are designed to encourage small energy producers, consumers, and prosumers to trade energy with one another in a market that is competitive and to balance local energy supply and demand. With the help of price signals, Transactive Energy (TE) markets manage distributed resources autonomously to maintain system stability. Through active Distributed Energy Resources (DERs) involvement, TE markets help increase the network's use of renewable energy. The increased number of DERs and local energy trading will improve the grid's overall operational efficiency. It alleviates the surges in wholesale energy market prices by lowering the peak-to-average demand ratio through local energy trading during peak hours. Market participants can engage in local energy trading and improve their welfare by selling/buying their energy at a higher/lower price because system operation costs rise during peak hours (due to higher demand). Additionally, a decrease in the commitment to and usage of centralised fossil fuels is responsible for the drop in greenhouse gas emissions. Fig 7 shows an example of a transactive energy trading mechanism.

TE markets focus on providing demand-side response [20], [21], demand-supply balance [22], response to grid constraints [23], and grid stability services [24] to achieve cost minimisation or profit maximisation. TE markets can also trade surplus energy in energy markets, which on individual participant level is smaller than the minimum bid size requirements of the energy market [25], [26].

The price formation mechanisms in TEM generally are single auction, double auction, the market operator determined, or negotiations based. Only agents on one side of the market exchange messages during a single auction. Examples of single auctions include demand response units bidding to provide flexibility or energy reduction services at a specific time and consumers in a community bidding to purchase units of excess renewable energy available at a particular time

[27]. Messages can be sent by both buyers and sellers in the double auction. Buyer bids convey a willingness to pay and reflect underlying preferences and utility. The seller requests communication of acceptance that takes into account underlying expenses [28], [29]. The double auction mechanism is widely used in energy and financial markets. In the operator-determined mechanism, the prices are set based on a pre-agreed or pre-set mechanism rather than bids or offers [30]. Examples include fixed feed-in tariffs or price as a function of demand or usage-based prices. The operators generally are community aggregators, local retailers or distribution network operators. The negotiations-based mechanisms are more decentralised based as they involve one-to-one offers being made and accepted between participants [31]. An autonomous AI-based algorithm/software manages the transactions. They are less structured price formation mechanisms compared to double auction mechanisms.
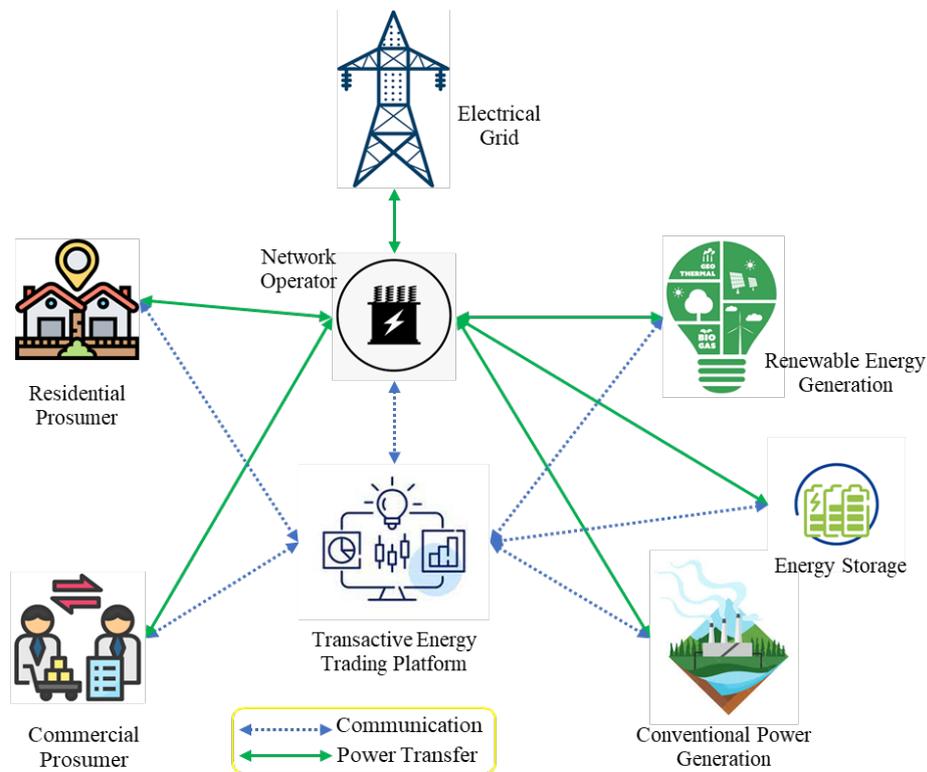
Fig 7: Transactive Energy Trading Mechanism

6. Research Gaps and Questions

Based on the review of the literature pertaining to the energy management system for the integration of EVs in the transactive energy markets, the following research gaps were identified:

1. There is a lack of a realistic energy management system regarding parameters and constraints.

   The transactive energy-based energy management systems in the literature primarily optimise for charging cost, network constraints and computational efficiency while not considering the EV's battery degradation, renewable energy generation and their

levelized cost. The EV user choice in trading bid formulation is also primarily neglected. EVs are an excellent storage medium for integrating renewable energy generation and optimising their use through transactive trading, which requires more research on this topic.

2. The forecasted input parameters are assumed to be perfect (or uncertainties are generally not considered) or assumed to be based on physical equations.

    The most common approach in the literature is to use physical equations or statistical distribution curves to generate parameters such as electrical loads, electricity prices and renewable energy generation. The renewable energy generation or EV user's charging behaviour or electricity prices are very uncertain, parameters mostly approximated by deterministic forecasting techniques. A robust energy management system must incorporate accurate forecasting of these parameters based on actual data, uncertainty, or probabilistic-based scenarios in modelling.

3. Realistic factor like range anxiety is not considered in designing the energy management system.

    Range anxiety is a significant barrier to the availability of EVs for transactive trading affecting charging management. The thesis models this essential variable and studies its impact on the transactive energy systems.

The research questions answered in this thesis are:

1. How can an optimal energy management system be designed for PV-based EV charging and transactive trading in an energy market environment?

2. How can the energy management system be improved for PV-based EV transactive trading by realistic assumption and incorporating charging parameters in an optimal trading algorithm?

3. How can the system uncertainties be specifically modelled to improve the accuracy of the developed optimal trading algorithm?

This research aims to design an optimal, advanced, computationally efficient energy management system for PV-based workplace EV charging under a transactive energy market environment.

The research methodology for designing a workplace Transactive Energy Management System (TEMS) for PV-integrated EV charging in this thesis is presented in Fig 8 and Fig 9. It comprises of four fundamental components, each addressing a critical aspect of the system's development. Firstly, the methodology entails the forecasting of crucial inputs, including PV generation, electricity prices, and EV charging demand. Accurate and precise forecasts of these parameters are essential for optimizing the workplace TEMS. Secondly, the research involves the modelling of the entire system, encompassing EVs, workplace charging infrastructure, and the various

uncertainties associated with energy generation, consumption, prices, and market dynamics. This modelling phase is critical in understanding the complex interactions within the system. The third component focuses on the design of a trading algorithm tailored to transactive energy markets. This algorithm governs the bids and auctions involved in energy transactions, promoting efficiency and equitable distribution. Lastly, the research methodology incorporates optimization techniques to minimize costs or maximize profit and enhance the utilization of PV-generated electricity. These optimization goals are central to achieving the economic and environmental objectives of the workplace TEMS, ensuring that it operates at its most efficient and sustainable capacity.
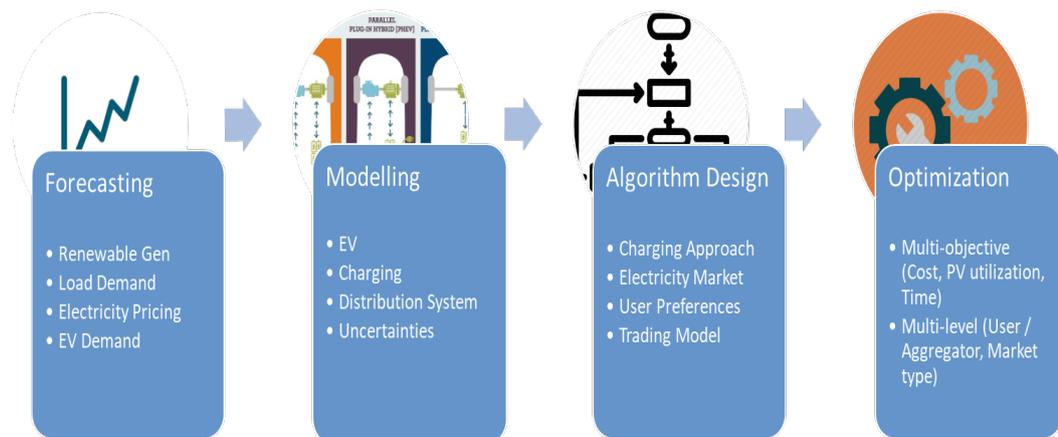
Fig 8: General research components of thesis
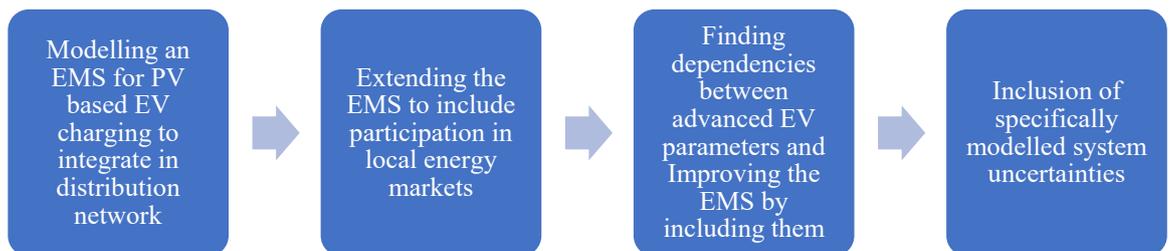
Fig 9: Research methodology of thesis

7. Thesis Structure

This PhD thesis follows the Auckland University of Technology (AUT) institution's doctoral thesis Format Two, also referred to as the "Manuscript Format". Therefore, apart from Chapter 1 & Chapter 6, the remaining chapters are presented in the manuscript format as submitted to the journals/conferences for publication. Hence, some repetitions can be found in the thesis. All the

manuscript-based chapters start with a preface to introduce them, followed by the chapter identical to the published/submitted manuscript.

Chapter 1 covers the general introduction of the thesis. Chapter 2 presents an in-depth analysis of the existing literature on the energy management system for PV-based grid-integrated EVs. An optimised transactive energy-based energy management system for PV-connected EVs is presented in Chapter 3. An optimal energy management system having a double-sided bidding-based transactive energy trading is presented in Chapter 4, incorporating system uncertainties. The transactive energy-based energy management system is advanced to feature range anxiety associated with EVs as a driving factor in Chapter 5. Finally, in Chapter 6, the thesis is concluded with research remarks and considerations for future research directions. The thesis structure is shown in Fig 10.
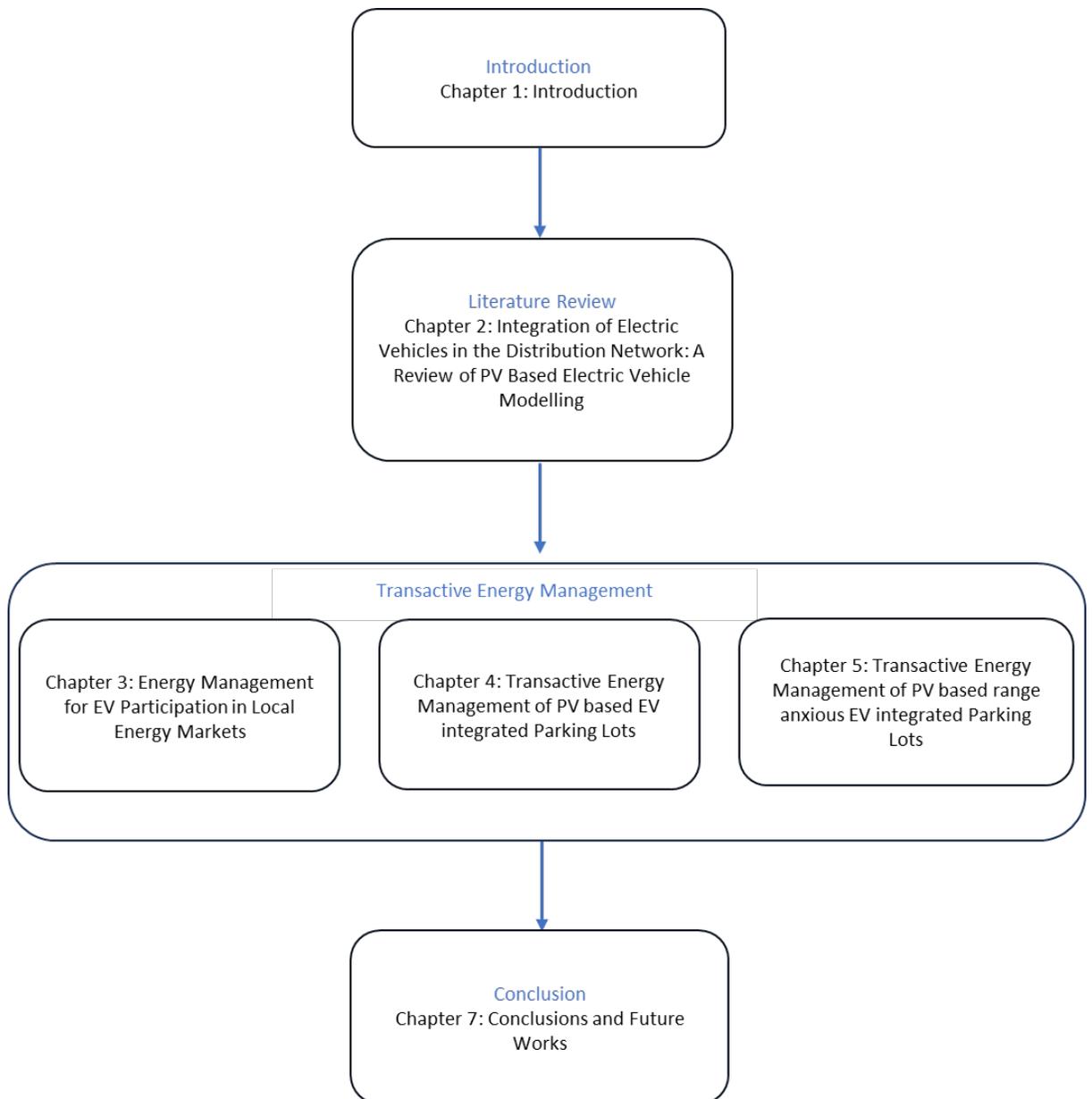
Fig 10: Thesis structure

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Chapter 2: Manuscript 1 - Literature Review

This manuscript presents a state-of-the-art comprehensive review of modelling techniques for the grid connected EV-PV system. It outlines a general framework for designing grid-connected EV-PV systems with a specific focus on smart charging algorithms. This manuscript offers an extensive examination of modeling a grid-connected EV-PV system, encompassing control architectures, charging algorithms, and uncertainty analysis. Its objective is to assess these elements, providing valuable insights for researchers interested in modeling grid-connected EV-PV systems. Such modeling is crucial for conducting impact studies or implementation assessments of electric vehicle integration into the distribution grid. The manuscript concludes with finding research gaps in this area and providing recommendations for future research. The manuscript recommends a need for more research on peer-to-peer or transactive type charging systems as these systems offer a potential to create a decentralized and democratized energy ecosystem where EVs not only consume electricity but also contribute excess energy back to the grid.

Integration of Electric vehicles in the distribution network: a review of EV-PV modelling

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Abstract: Electric Vehicles (EVs) are one of a prominent solution for the sustainability issues needing dire attention like global warming, depleting fossil fuel reserves, and greenhouse gas (GHG) emissions. Conversely, EVs are shown to emit higher emissions (measured from source to tailpipe) for the fossil fuel-based countries, which necessitates Renewable Energy Sources (RES) for maximizing EV benefits. EVs can also act as a storage system, to mitigate the challenges associated with RES and to provide the grid with ancillary services such as voltage regulation, frequency regulation, spinning reserve, etc. For extracting maximum benefits from EVs and minimizing the associated impact on the distribution network, modelling optimal integration of EVs in the network is required. This paper focuses on reviewing the state-of-the-art literature on the modelling of grid connected EV-PV (Photovoltaics) system. Further, the paper evaluates the uncertainty modelling methods associated with various parameters related to the grid connected EV-PV system. Finally, the review is concluded with a summary of potential research directions in this area. The paper presents an evaluation of different modelling components of grid connected EV-PV system to facilitate readers in modelling such system for researching EV-PV integration in the distribution network.

Keywords: Plug-in electric vehicle; Energy management system; Renewable energy; Vehicle-to-grid

1. Introduction

The issues like global warming, depleting fossil fuel reserves, and greenhouse gas (GHG) emissions need dire attention for ensuring a sustainable future. Because the transportation sector is one of the largest contributors to the rising harmful emissions, the electrification of transportation is seen as a promising solution for this problem. The Electric Vehicle (EV) technology has existed for more than a century peaking commercially around 1900. However, due to the easy availability of fossil fuels, advancements in Internal Combustion (IC) technology, and simplicity in the use of IC engines, EVs were put on hold and limited to golf carts and delivery vehicles. Figure 1 shows the progression timeline of the EVs. The dependency on petroleum imports for transportation purposes is also reduced by electrification of transportation, thereby increasing energy security. However, the adoption rate of EVs remains slow owing to factors such as high initial cost, battery degradation, inadequate charging infrastructure, range anxiety, etc [1]. Various policies and incentives are made available by governments around the world to promote

the uptake of EV and to prevent these barriers from realizing a complete shift to electrified transportation. As per the report "Global EV outlook" of the International Energy Agency, the total number of EVs are projected to reach 130 million by 2030 [2].

However, high penetration of EVs also poses distribution network quality issues, particularly network congestion, three-phase voltage imbalance and off-nominal frequency problems. The EVs are a mobile single-phase load so they can be randomly plugged in at any one of three phases within distribution networks, leading to a scenario that electrical components in one particular phase such as power supply cable, overhead line or transformer may be heavily loaded while the rest of two phases are not. The unbalanced three-phase loading may lead to a series of negative impact on power quality issue: transformer failures, equipment loss-of-life, relay misfunction, etc. Also, as EVs are highly spatial and temporally uncertain, handling EVs as additional loads while maintaining the reliability and security of the grid is difficult. The coincidence of timing between EV home charging and residential load peaks leads to additional system peaks. Moreover, multiple EV chargers in a neighbourhood can introduce significant harmonics thereby reducing power quality [3]. Therefore, the integration of substantial EV penetration in the distribution networks is a significant area of interest in the research and engineering community, especially optimally controlling EV charging to minimize the impact of the above described issues.
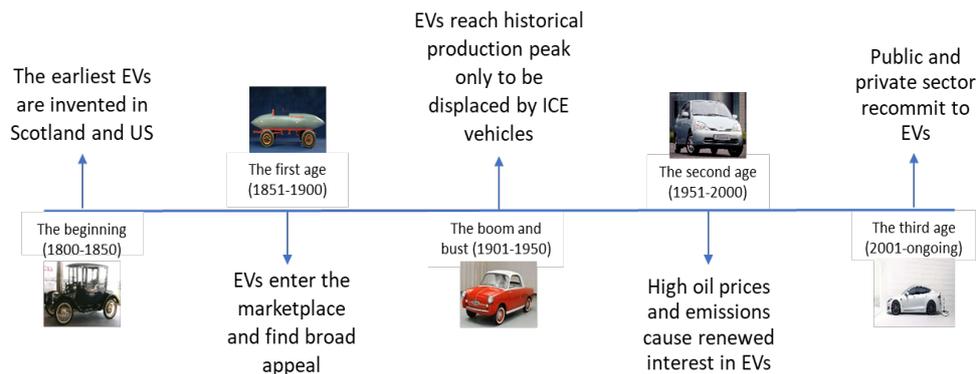
Figure 1. The evolution of EVs

Another significant contributor to harmful emissions is the power industry particularly fossil fuel-based power generation. Renewable Energy Sources (RES) such as wind and solar are increasingly adopted to mitigate the power industry emissions. The variable nature of RES which depends on the weather, time, location, etc. creates voltage stability and reliability issues for the power grid requiring integration of Energy Storage System (ESS). Also, there may not be sufficient demand requirement during the period of high RES generation which leads to the under-utilization of average generated capacity. Using ESS with RES can result in its effective utilization as ESS can store energy when demand is low and supply back when demand is high. Apart from using ESS, application of demand-side management techniques like load shifting, time of use pricing, and demand bidding can also solve the aforementioned problems associated with RES although the impact of these techniques is limited compared to ESS [4,5].

A large-scale integration of RES requires an increased size (or capacity) of ESS. Hence, it leads to a significant capital requirement especially due to the high per-unit cost of ESS. As we are already moving towards electric vehicles to combat GHG emissions and these EVs essentially run on the batteries, the EVs can also act as a dynamic natured ESS due to the Vehicle-to-Grid (V2G) feature, in which EVs deliver energy stored in their batteries back to the grid [6]. Additionally, EVs spend a considerable amount of time (22 hrs) in parked conditions [7], so they can be suitably used as ESS without creating inconvenience (e.g., range anxiety issues) for users. However, battery degradation is still an issue which can be offset by giving incentives to users/aggregators to participate in V2G. As the battery capacity of each EV is minuscule compared to grid load requirements, an aggregation of EVs is generally required to provide the grid with the backup power. Apart from storing surplus energy generated by RES, EVs can also provide the grid with additional ancillary services such as voltage regulation, frequency regulation, spinning reserve, etc. EVs can also participate in energy trading, to be a source of revenue for the aggregator/users to compensate for the battery degradation due to participation in V2G. However, most of the energy markets around the world require a minimum capacity to participate which would require an aggregator of a large number of EVs. To counteract this, more research is being done on transactive or Peer-to-Peer (P2P) trading mechanisms [8].

Moreover, the emission benefits of electrified transportation cannot be maximized if the source of EV charging is based on non-renewable sources. In fact, EVs are shown to emit higher emissions, measured from well to wheel i.e., source to the tailpipe for the countries whose primary source of power generation is based on fossil fuels [9]. However, using RES to charge the EVs could result in reducing GHG emissions as shown in [10] where 50000 EVs charged from a mix of wind and PV energy sources resulted in 400 Mtons less emissions per year.

Based on these factors, this paper presents a general framework for designing a grid connected EV-PV system. Several papers have also reviewed the different aspects of the interaction of EV-PV system and distribution network in the literature. Refs [11–14] discuss charging EVs using PV generation with a focus on control architectures and algorithms, and economic framework. The impact of the charging infrastructure of EV on the grid in terms of power quality is reviewed in [15]. An overview of EV modelling techniques is presented in [16–18] with an emphasis on modelling methods for EV loads and charging stations.

These review papers study the limited aspects of the interaction of grid connected EV with RES, particularly PV, focusing on the modelling of control methods or EV loads. Also, a detailed review of modelling the uncertainties present in the grid connected EV-PV system is not present in literature to the knowledge of the authors. Therefore, this paper presents a comprehensive review of all aspects of modelling a grid connected EV-PV system viz., control architectures, charging algorithms, and uncertainty analysis. This paper aims to provide an evaluation of these aspects to enable the researchers to model a grid connected EV-PV system for carrying out impact or implementation studies of EV integration into the distribution system. The grid is represented

by a distribution network as EV and PV both are on the distribution side. Throughout the paper, EV-PV system is considered as a single entity (limited to the times when connected to the grid for charging or vehicle-to-grid) and the PV is considered as a complementary energy source to charge EVs other than the grid. Figure 2 shows the analytical framework of the modelling aspects of grid connected EV-PV system.
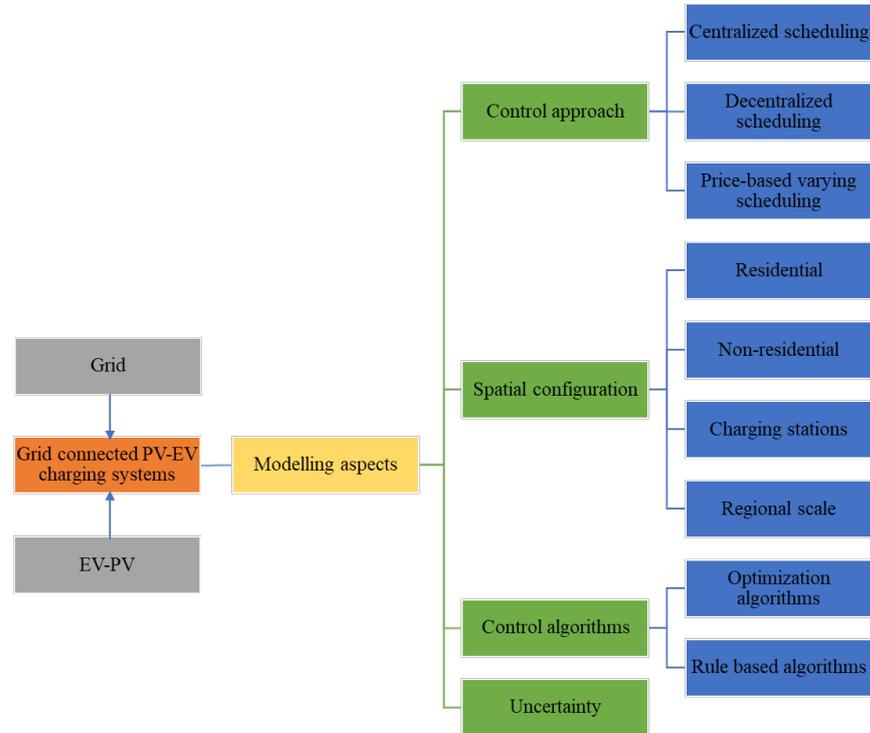
Figure 2. An analytical framework for grid connected EV-PV interaction

The organization of the paper is as follows: Section 2 provides an overview of the modes of EV integration with the grid. Section 3 discusses the control architectures of connecting EVs to the grid. Section 4 describes the state-of-the-art literature of smart charging algorithms of grid connected EV-PV system. Section 5 reviews the uncertainty analysis methods for EV demand, PV generation, and load distribution. The suggestions for future research with concluding remarks are presented in Section 6.

2. EV interaction with the distribution network

Figure 3 shows a general representation of an EV connected to the electrical grid. The technology which allows the bidirectional flow of energy between EV and grid is known as Vehicle-to-Grid (V2G). It is achieved by the integration of Information and Communication Technologies (ICT) with the EV charging system. The modelling research of EV interaction with the distribution network has transitioned from unidirectional mode in the initial stage to bidirectional mode in the current stage [6], [7].
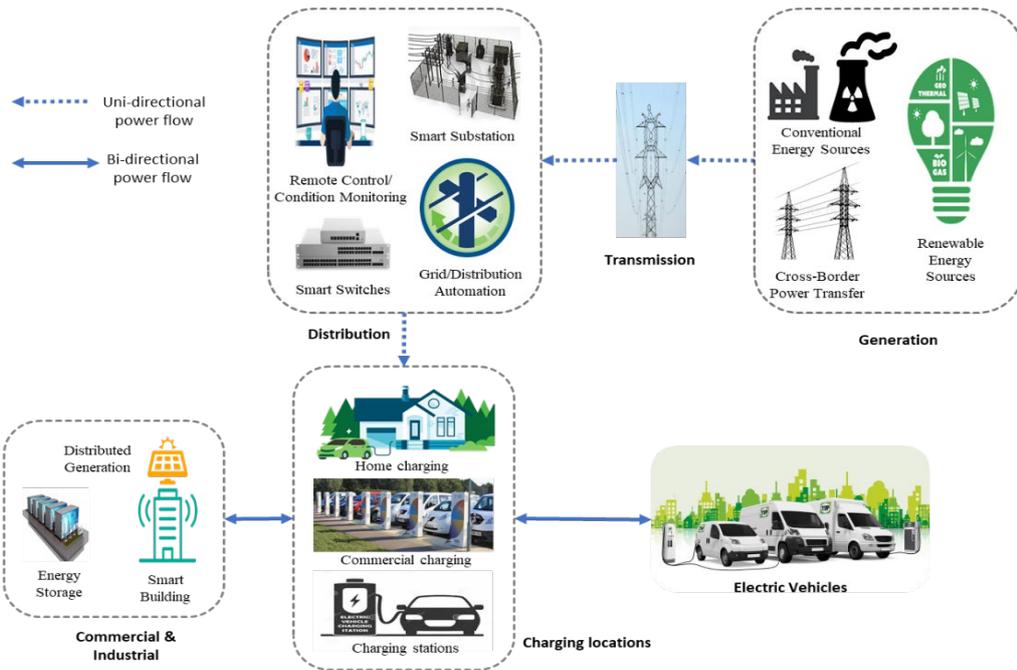
Figure 3. EV integration with the electrical grid

With the increasing level of EV penetration, the associated technical issues e.g., system imbalance, decreased stability, and power quality, as well as increased system cost, are becoming more prominent due to additional energy and power demand. The unidirectional approach i.e., G2V mode has been extensively studied in the literature in the form of topics like smart charging [19], safety [20], and control features [21]. The focus of these studies is on minimizing the charging cost [22] or minimizing the impact on the distribution system [23], [24].

However, in the bidirectional mode, EV is not only the load for the grid but also a distributed generation and storage. The initial idea was to use EV battery to store energy and send it back to the grid in peak period, known as peak load shaving [6]. Ref [25] presents a review of peak shaving strategies using demand-side management, energy storage systems, and electric vehicles. Table 1 illustrates the characteristical differences between the unidirectional and bidirectional modes. As an individual EV has a small battery capacity, a major challenge is the synchronization of a large number of EVs charging/discharging operation required for them to be an effective storage system. Also, the limited uptake of EV didn't quite make this idea of using EV in the bidirectional mode mainstream. Research later indicated that the application of bidirectional V2G in the ancillary market: spinning reserve and voltage control is much more important than peak load reduction. Spinning reserve is the extra generation that can be made readily available and it is paid for the availability along with the time it is called for deployment (compared to peak load shaving), which makes deployment of EV in ancillary service provision very economically favourable. Also, in terms of frequency of deployment, the voltage regulation is needed more than 300 times per day compared to the need for peak load shaving which is only a few hundred hours per year [26].

Table 1. Modes of Interaction between EV and grid

Features	Unidirectional	Bidirectional
Power flow	Grid-to-Vehicle (G2V)	G2V & V2G
Infrastructure	Communication	Communication, bidirectional charger
Cost	Low	High
Complexity	Low	High
Services	Load profile management, Frequency regulation [27]	Backup power support, frequency regulation, voltage regulation, active power support [28]
Advantages	Overloading prevention, load levelling, profit maximization, emission minimization [29]	Overloading prevention, profit maximization, emission minimization, RES integration, voltage profile improvement, harmonic filtering [30], load levelling, power loss reduction [31]
Disadvantages	Limited services	Battery degradation, high complexity, and cost, social barriers

Initially, V2G involved only energy transfer from EVs to the distribution system. However, with the advancement in technology, two new energy transfer modes (V2H and V2V) are added. Therefore, the bi-directional energy transfer from EV can now be classified into:

- Vehicle-to-Grid (V2G): Energy transfer from EV to the distribution network.

- Vehicle-to-Home/Building (V2H/V2B): Energy transfer from EV to home/building.

- Vehicle-to-Vehicle (V2V): Energy transfer from one EV to another EV.

3. Modelling of grid connected EV-PV system

The sustainability of EV depends on the source of charging. All forms of EVs viz., Plugin Electric Vehicle (PEV), Hybrid Electric Vehicle (HEV), or Plugin Hybrid Electric Vehicle (PHEV) have lower emissions if the energy supplied for charging is based on clean fuel, such as renewable sources. However, contrary to popular belief if the EVs are charged from fossil fuel or gas-based generation, the emissions are significant and not zero. The RES i.e., PV, wind, tidal, geothermal, or hydro are excellent options to power electric vehicles. Moreover, the following reasons make PV an admirable source to charge the EVs:

The cost of PV has been dropping continuously and is currently less than $1/W_p$ [32].

- PV is highly accessible i.e., PV modules are generally installed on the building rooftops and carparks, close to EV locations.

- PV modules do not require maintenance and are also noise-free.

- EVs can store the surplus generated solar energy thereby eliminating the need for battery systems [33,34].
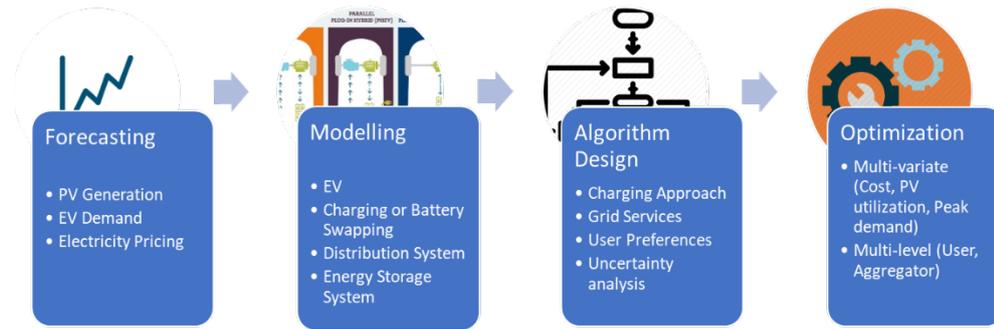
Figure 4. A general outline for modelling a grid connected EV-PV charging system

Figure 4 shows a general framework for designing a smart charging system for integrating EV-PV system into the grid. As the focus of this review paper is on modelling aspect of the grid connected EV-PV system, this section will provide an overview of the modelling of control approaches with subsequent sections reviewing about charging models/algorithms and uncertainty.

The control architectures for grid connected EVs (with or without PVs) can be categorized into the following three methodologies:

- Centralized Scheduling
- Decentralized Scheduling
- Price varying Scheduling

In centralized scheduling method, EV aggregator plays a crucial role in integrating EV with the grid. Initially, each EV sends the necessary charging related information to the aggregator. After which aggregator computes the optimal charging strategy and participates in the energy trading through bidding which is verified by grid system operators. The general objective functions in centralized type scheduling are charging cost minimization [35], line power loss minimization [36], aggregator profit maximization [37,38], voltage regulation [39] and frequency regulation [40]. Due to the aggregation of many EVs, this method is very good for providing backup power and ancillary services. However, in the centralized method, EV users have to relinquish the charging process control to centralized authority. Other drawbacks of this approach are high dependency on the control centre and large communication bandwidth.

In decentralized scheduling method, individual EVs are controlled directly instead of through a central control unit. Firstly, EV aggregator formulates a bidding strategy based on EV load demand data collected or forecasted in a given period. Then, the bids are submitted to the central grid operator and cleared in the energy market the same as in centralized scheduling. After the bids are approved and an agreement is done with the grid operator, the aggregator broadcasts the charging prices to individual EV users. Based on the price and convenience, users decide whether to charge/discharge their EVs in a given period. The advantage of this type of scheduling is that

the infrastructure is simple and of low cost. However, due to a random number of EVs guaranteed to be available at a given time, this method's capability of the provision of backup power and ancillary services is low. Also, privacy and security issues are there. The general objective function in decentralized type scheduling is mainly charging cost minimization [41–43]. Other objectives are RES integration [44], load profile levelling [45], voltage regulation [46] and frequency regulation [47].

The price varying scheduling has the same structure as decentralized scheduling, however, the charging behaviours of EVs are directly affected by varying electricity pricing. Instead of two-way communication i.e., price and power schedule information exchanged in decentralized scheduling, here the only price is communicated to EVs. Ref [48] discusses the feasibility of using Time-of-Use (TOU) based pricing for EV energy management. Ref [49] presents a socially optimal pricing system between EV aggregators and utility. Ref [50] introduces a smart EV energy management algorithm that takes dynamic factors such as user participation and load variation into account.

Figure 5 presents an overview of the comparison between the scheduling strategies discussed above [51]. Even though the price varying scheduling is overall less complex, it is less attractive for commercial entities to participate in V2G due to the high cost of computation on their side. Hence, the focus of research is generally more on centralized and decentralized scheduling strategies.

The grid connected EV-PV systems are designed based on spatial configuration requirements i.e., for homes or office use etc. Generally, in literature four space-based levels are used: residential (individual house), non-residential (commercial/workplaces), public charging stations and inter-territory region. Due to the large size of EV loads, which almost doubles the electricity consumption of a household, it is reasonable to provide another energy source (like PV) [52]. Nevertheless, it appears through the literature that while coupling EV with PV inside households can be beneficial, the benefits are bounded by the EV utilization for mobility. Most of the EVs are usually away from home during the day and therefore cannot benefit from maximal PV generation. It is reasonable to assume that usually, EVs will be at non-residential places (commercial/workplaces) during this day period when peak PV generation happens. So, EVs will be either at residential or non-residential areas. Therefore, the focus of this paper is only on the modelling of residential and non-residential (commercial/workplace) EV-PV system. The PV based EV charging stations are not yet economically feasible due to the marginal cost associated with PV generation and the cost of energy storage systems [53]. Ref [54] is one example of the limited literature available on standalone PV based EV charging stations.
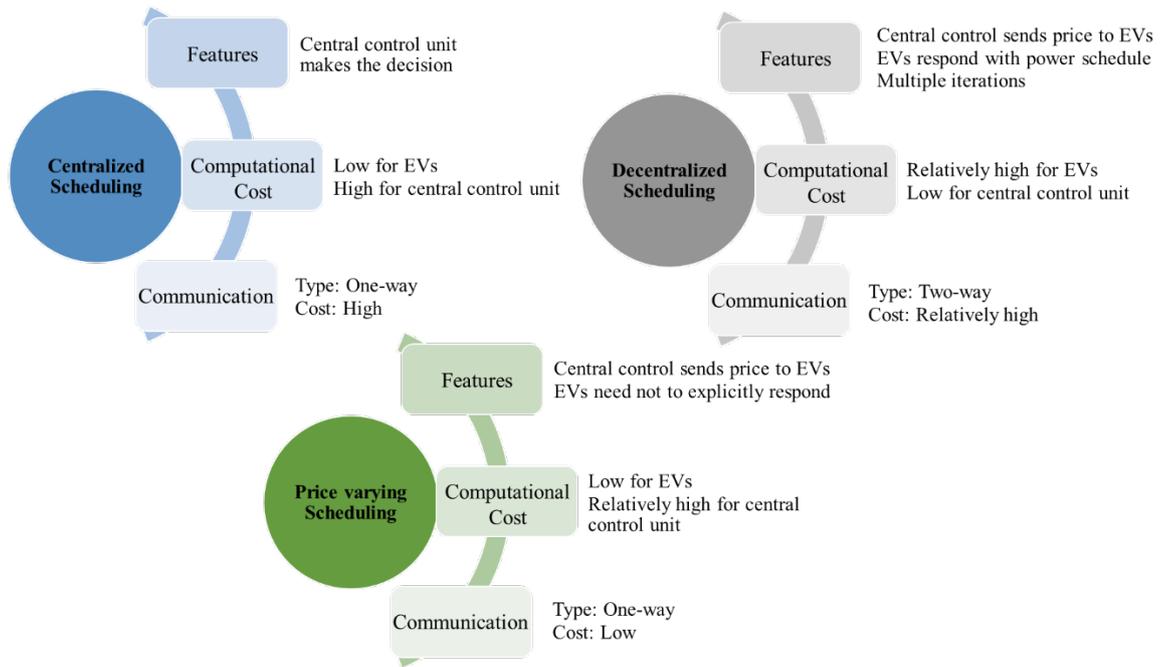
Figure 5. An overview of scheduling strategies in V2G mode [51]

4. EV smart charging using PV and grid

Multiple studies have explored the advantages of a PV based EV charging system. Ref [55] demonstrates the advantage of using PV to charge the EV and show that it allows for greater penetration of both PV and EV. EVs can also mitigate the negative effects of excess PV generation [56]. Ref [57] presents a case study of Columbus, USA, in which it is demonstrated that charging EV from the PV is more economical and produces less CO_2 footprint than charging EV from the grid. A case study presented in [58] compares charging of EVs through the modes: only grid, only PV with battery storage and grid integrated PV and finds that the grid integrated PV performs better economically compared to the other two systems. In [59], the authors discuss the application of PV energy and EV as an energy storage system to mitigate the peak loading in the grid. These studies demonstrate the advantages of PV based EV charging over grid EV charging. There is a vast amount of literature on different charging algorithms or achieving different economic, technical, or social objectives related to PV based EV charging. Table 2 provides a summary of key smart charging related works for the grid connected EV-PV system. The optimization model type depends on the problem formulation. Generally, the convex type problems (linear, mixed-integer, quadratic) can achieve optimal solutions with a low computational cost. For non-convex problems, meta-heuristic type optimization methods (Genetic Algorithm, Particle Swarm Optimization) are useful to achieve a near-optimal solution with a low computational burden. The rule-based algorithm or heuristic type optimization methods can produce good enough solutions for random instantaneous events (e.g., plugging/unplugging of EVs, PV power variation) with little data and computational power requirements. The focus of the literature is generally on residential or office PV based EV charging system, not on commercial applications due to less complexity in analysis and modular

integration in the distribution system. Also, almost all the smart charging research focuses on the specific aspects of optimizing the EV integration into grid e.g., slow/fast charging, market participation, ancillary services. For emulating the real-life implementation, a comprehensive system with multiple aspects is required. Ref [60,61] are some early stages work on a comprehensive system combining multiple aspects which are usually studied in isolation.

Table 2. Summary of literature related to smart charging of grid connected EV-PV system

Ref	Objectives	Optimization model	Software/Implementation	Key findings
[62]	Peak shaving and valley filling	Linear programming	MATLAB	The effectiveness of the proposed algorithm is dependent on a high number of available parking spots.
[35]	Maximizing profit and PV utilization	Mixed Integer Linear programming	GAMS	Due to battery degradation cost, V2G is not economically feasible unless high PV production is present
[63]	Minimizing system cost	Mixed Integer Linear programming	CPLEX	Smart charging can result in saving of operational cost for charging and PV usage for the parking lot owner
[64]	Minimizing charging cost	Fuzzy logic	MATLAB	The algorithm is not optimization based so targets several objectives: reduction in charging cost and system losses, improvement in voltage profile.
[65]	Maximizing PV utilization	Metaheuristic	MATLAB	The proposed heuristic algorithm achieves desired objectives with low computational cost and without forecasting of uncertain variables.
[66]	Maximizing EV aggregator benefits	Hybrid MPC	-	The proposed algorithm achieves near-optimal solution of EV charge scheduling problem with better efficiency than standard MPC
[67]	Maximizing PV utilization and reducing EV charging impact	Linear programming	Case study: New South Wales distribution system	The proposed strategy controls the charging/discharging profile of EVs to match with the shape of the PV output to achieve desired objectives.
[68]	Minimizing charging cost	Mixed Integer Linear programming	Case study: Korea	The proposed algorithm does not consider selling excess power and demonstrates charging cost savings compared to uncoordinated charging
[61]	Minimizing system cost	Mixed Integer Linear programming	Microsoft Solver Foundation	A comprehensive system to achieve one optimal charging profile will result in a larger net benefit compared to individual applications.
[69]	Minimizing charging cost	Convex programming	MATLAB	ESS can significantly reduce charging cost and bi-directional V2H is cheaper than H2V
[70]	Maximizing profit and ESS life	Non-linear programming	GAMS	Considering only revenue maximization will result in an adverse effect on ESS life
[71]	Maximizing PV utilization	Linear programming	Case study: LomboXnet	Proposed algorithm increases PV self-consumption and reduces peak demand by half
[72]	Minimizing charging cost	Rule-based algorithm	MATLAB	Rule-based charging is superior to conventional charging for less charging cost and reduced grid loading

[73]	Maximizing PV utilization	Rule-based algorithm	MATLAB	V2B can be an effective strategy if initial capital costs and electricity price are fitting
[74]	Minimizing peak demand	MPC	MATLAB	EV scheduling can reduce both the magnitude and frequency of peak loading
[75]	Peak shaving and valley filling	Quadratic programming	MATLAB	Net load variation was lower in case of low PV power-sharing and vice-versa

V2H: Vehicle-to-Home; H2V: Home-to-Vehicle; V2B: Vehicle-to-Building; MPC: Model Predictive Control

The stochastic behaviour of the PV generation is a major disadvantage for EV charging. The approach of a smart charging algorithm is to provide flexibility in EV charging to account for the uncertainty in PV generation. Ref [71] has shown that smart charging along with the V2G technology increases PV self-consumption and reduces peak demand. Ref [76] varies the EV charging power with time to match with the generated PV power and achieves the condition of maximum PV utilization. Another way to counteract uncertainty is the sequential charging in which the total number of EVs charging at constant power is varied dynamically so that the net charging power follows the PV generation, as seen in [77]. Ref [78] considers multiple cases to show the superiority of sequential charging over concurrent charging in terms of PV utilization under stochastic conditions. However, due to no associated time constraints, it is not feasible for workplace charging.

5. Uncertainty modelling

This section reviews the methods for modelling the uncertainties present with the various input parameters for the EV-PV grid integrated system. Three input factors are of main interest: EV charging demand, PV generation, and Electrical load distribution. The tables in respective sections summarize the techniques used to model the uncertainties present. The remarks show the comparative analyses of these techniques in terms of system size, computational cost, and accuracy.

5.1. EV charging demand

The uncertainties in EV charging demand are due to multiple factors e.g., user behaviour, charging infrastructure, and operational parameters. Table 3 presents an overview of various uncertainty methods for modelling EV load demand in terms of application and associated drawbacks. Generally, Monte Carlo and Probability distribution based modelling method is common practice in the literature. However, due to computational cost and accuracy issues associated with them respectively, more advanced methods like Markov chain and Information gap decision theory are used for specific applications. A hybrid approach of combining methods is also used to minimize the associated drawbacks.

Table 3. Overview of uncertainty modelling methods for EV load demand

Method	Remarks	Ref
Scenario reduction	• Simple and less computationally intensive • Approximate uncertainty modelling, accuracy depends on the amount of historical data available	[79,80]
Monte Carlo simulation	• High accuracy but also computationally intensive • Accuracy depends on the amount of historical data available	[19,81]
Fuzzy logic	• Historical data not required • Accuracy depends on rule settings which are based on researcher experience	[82,83]
Hybrid Monte Carlo-fuzzy	• High accuracy but also computationally intensive • Can model both temporal and spatial uncertainty	[84]
Artificial Neural Network	• Accuracy depends on input dataset quality • Considers the correlation between forecasted and observed data	[37,85]
Markov chain	• Very high accuracy with moderate computational cost • Performance depends on input data dimension	[86]
Probability distribution fitting	• Very simple but also less accurate	[87,88]
Robust optimization	• Low computationally intensive however difficult to employ with nonlinear problems • Not flexible i.e. give a single solution which might be infeasible	[89,90]
Information gap decision theory	• Useful for dealing with severe uncertainties • Complex implementation	[91,92]

Figure 6 shows the various input parameters for the uncertainty modelling of EV load demand. The parameters related to time (e.g., arrival, departure, travel, service) and charging power demand required are common in all the three modes of charging: individual, residential, and commercial, while others are specific to the application. The uncertainties in the parameters involving human factors i.e., travel/arrival/departure time and pattern are difficult to describe accurately, and also the literature is quite scarce on the effect of human learning capability on EV charging demand. Ref [44] is an example of paucity of research on the practical effect of human factors on EV charging.
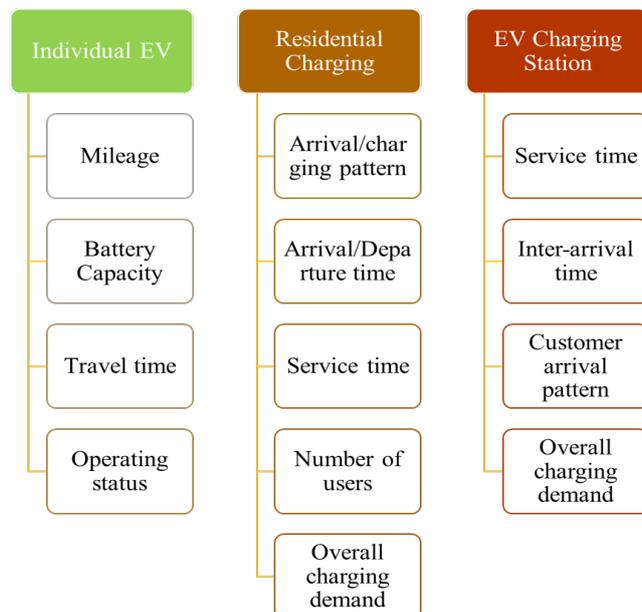
Figure 6. EV load demand parameters used for uncertainty modelling

5.2. PV generation

A PV module converts energy from the sun into electrical form depending upon the incident radiation on the module surface. This incident solar radiation is highly variable and depends on various geographical and metrological factors. The common variables used in uncertainty modelling of PV generation are solar irradiance, sky type index (clear, cloudy, sunny), module and air temperature, wind speed, and humidity. Table 4 shows a summary of commonly used uncertainty modelling methods for PV generation. The commonly practiced methods are Point estimation, Monte Carlo, Scenario based analysis, and statistical methods (Autoregressive Moving Average). These methods are less complex and work well with small system size. However, for bigger PV systems, Rolling Horizon approach and Kernal Density are more suitable. Generative Adversarial Network (GAN) is the latest uncertainty modelling method based on a machine learning approach.

Table 4. Overview of common uncertainty modelling methods for PV

Method	Remarks	Ref
Point estimation	• Computationally intensive with more input variables	[93]
Bootstrap	• Simple and low computational cost • High accuracy	[94]
Monte Carlo simulation	• High accuracy but also computationally intensive	[95]
Mean-Variance estimation	• Based on the assumption that uncertainty is normally distributed • Simple but less accurate for practical cases	[96]
Two stage scheduling	• Upper level deals with global adjustment and lower with local adjustment • Simple, flexible and accurate	[97]
Scenario based analysis	• Very commonly used method with a high degree of accuracy • Accuracy depends upon the scenario generation technique	[98]
Kernel Density estimation	• Needs to analyze a large amount of historical data	[99]
Autoregressive Moving Average	• Accuracy depends on historical time-series dataset • Needs a lot of historical data and analysis	[35]
Probability distribution fitting	• Very simple but also less accurate	[100]
Rolling Horizon approach	• Effective for large scale system with moderate computational cost	[101]
Generative Adversarial network	• Very new and highly accurate scenario based method	[102]

Ref [103,104] describes the implementation details of various forecasting techniques for PV power generation. More details about uncertainty modelling for the RES systems can be found in [105–108]. The literature of PV based uncertainty modelling is scarce as the cumulative effect of PV power on the system is small compared to other uncertain variables (load, EV demand).

The most common method to mitigate the PV uncertainty is using an external battery storage system i.e., different from the EV batteries [109]. The excess PV generation, usually in the afternoon, is stored in the battery pack and used to charge the EVs when PV generation is

inadequate. Ref [110] compares three different algorithms for finding the best operation characteristics for the battery storage and finds that using a sigmoid function-based discharging algorithm while charging EVs during the night and storing PV excess is the best approach. However, these studies do not consider the optimal sizing of the external battery storage system as it is a quite expensive component. Apart from mitigating PV uncertainty, the external battery storage system also minimizes the impact of EV demand uncertainty parameters constrained by time.

5.3. Electrical load demand

The consumption of electricity is highly spatially and temporally uncertain, varying between different load sources, seasons, and the time of day. The main factors for introducing uncertainty in load sources are user behaviours, climatic conditions, and electrical equipment variation [111]. Table 5 shows an overview of various common methods used for modelling uncertainty in electrical loads. Readers can refer to [105,108,111–113] for implementation details of these and other methods used to model uncertainties present in electrical load. The convolution and cumulant based techniques are traditional methods popular in the late nineties' era. However, with the scaling of computational cost with system size, the point estimation became a more popular method. Monte Carlo and Scenario based analysis are also fairly common in literature.

Table 5. Overview of common uncertainty modelling methods for electrical load demand

Method	Remarks	Ref
Point estimation	• Does not require complete knowledge about the system but computationally intensive with more input variables • Two-point is the simplest and three-point is most efficient	[114,115]
Monte Carlo simulation	• High accuracy but also computationally intensive • Different sampling techniques reduce the computational burden	[116,117]
Fuzzy logic	• Less computationally intensive and robust in nature • Vital parameters are decided by the researcher based on experience	[118]
Scenario based analysis	• Very commonly used method with a high degree of accuracy • Accuracy depends upon the scenario generation technique	[119]
Autoregressive Moving Average	• Accuracy depends on historical time-series dataset • Needs a lot of historical data and analysis	[85,120]
Convolution based	• Traditional analytical method with low computation efficiency • Applicable to linear systems with independent inputs	[121,122]
Probability distribution fitting	• Very simple but also less accurate	[88,123]
Cumulant based	• Traditional analytical method with high computation efficiency • Accuracy decreases with higher order systems	[124]

6. Conclusion and future research suggestions

Electric vehicles and renewable energy-based generation are a promising solution to rising GHG emissions. Further, EVs can act as a dynamic energy storage system through the technology of V2G, thereby, facilitating RES integration in the smart grid. Also, well to wheel emissions from EVs depend upon the charging source. Therefore, RES based EV charging is desired for the overall reduction in emissions and getting the best of both technologies. Thus, this research area

is quite popular and needs further exploration for worldwide implementation. This paper presents a state-of-the-art comprehensive review of the modelling of grid connected EV-PV charging systems. A general framework of designing the grid connected EV-PV system is described along with a focus on smart charging algorithms. The modelling techniques for associated uncertainties with the grid connected EV-PV system i.e., EV demand, electrical load, and PV generation are also intensely reviewed. The study reveals although the research in this area is plentiful, few gaps need to be investigated. Some future research directions are suggested as following:

- Smart charging algorithms

  The EV charging models need to be more comprehensive in nature i.e., multiple charging powers, charging station & battery-swapping station, wholesale market trading & ancillary services provision so as to more accurately and realistically model the practical implementation. More studies with respect to finding the optimal trade-offs between computational burden and performance should be made.

- P2P V2G power transfer

  There is a need for more research on peer-to-peer or transactive type charging systems as this encourages all types (big, small, etc) EV aggregators to trade energy with one another instead of only sizeable aggregator participating in central energy trading. Another advantage is that transactive trading can operate independently of direct influence from the grid so that the price signal from the central power station may not affect the performance of the transactive trading the way it influences the scheduling and trading of energy in existing systems.

- Uncertainty analysis

  The focus of future research should be on finding more realistic forecasting and uncertainty analysis techniques that optimally balance simplicity and performance. Also, more advancement is needed in the modelling of challenging variables like human behaviour, etc. Further, almost all the current research focuses on improving PV forecasting accuracy rather than addressing uncertainties associated with PV generation.

- PV based EV charging stations

  With PV based EV charging being a viable solution for emission issues, more research is needed on the commercial aspects e.g., solar charging stations as current research focus more on residential EV-PV systems. The impact analysis and interaction with the distribution system needs to be studied in detail.

- Price varying scheduling

  Because of easy implementation and effectiveness for managing charging load in peak/valley times, price varying scheduling is very attractive to aggregators. Therefore, more research is required for charging models based on price response and price elasticity.

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Chapter 3: Manuscript 2 – Local Energy Markets

This manuscript presents a Local Energy Market (LEM) framework tailored for community houses with both electric vehicle (EV) charging and rooftop photovoltaic (PV) systems. LEMs present an intricate challenge due to the varying objectives of participants, but this manuscript establishes a novel approach for trading within the LEM and its connection to the wholesale energy market, facilitated by an aggregator, who enables the exchange of required energy and surplus energy between the LEM and the wholesale market. The LEM framework is constructed as an optimization challenge using the Grey Wolf Optimization algorithm, ensuring privacy considerations are addressed. The LEM participants are driven by the goal of maximizing their profits, and the market equilibrium is determined through a bidding process. The manuscript delves into the analysis of how changes in the aggregator's tariff impact the cost of EV charging, providing valuable insights into the economic dynamics of this integrated energy system. Remarkably, the LEM demonstrates the potential to enhance agent profits across different aggregator tariff settings.

Energy Management for EV Participation In Local Energy Markets

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Abstract—**Increasing penetration of renewable energy sources in the distribution system is leading to issues like costly system upgrades, low power quality and underutilization of renewable generation capacity. Local energy markets (LEM) are seen as a promising solution to these problems. Nonetheless, the integration and coordination of local markets into existing market structures is still an ongoing research problem. This paper proposes a LEM structure for community houses equipped with EV charging and rooftop photovoltaic (PV). The LEM system is formulated as an optimization problem with participants aiming to maximize profits while characterizing the market-clearing by the bid process. Moreover, an aggregator is established to integrate the LEM with the wholesale market and to maintain the trading of energy required and excess energy between LEM and the wholesale market. The impact of variation of aggregator tariff on charging cost is analysed.**

Keywords—Energy management system, Grey wolf optimization, Local energy market, Electric vehicles

INTRODUCTION

The increased proliferation of the distributed generation is leading to decarbonization and decentralization of the traditional power systems, as well as inspiring the proposition of new trading models [1]. One of these market models is local electricity markets (LEM), which provides a new structure for participants to trade mostly renewable energy, thereby lowering carbon emissions. This market system empowers the end-users to be proactive in the energy community. It promotes a sustainable power system [2]. The competition fostered by LEMs, specifically between the agents (or market participants), allows local small producers and prosumers to achieve more significant cost benefits than the current feed-in tariff policies. Further, increased trading in LEM leads to the deferment of costly network upgrades. It reduces T&D losses leading to increased overall operational efficiency [2].

Considering the high penetration of these distributed generations (PV) and idle EVs at smart parking lots, their cooperation in the form of integrated electric vehicle fleets and solar distributed generations would be beneficial for both sides since not only the green solar energy usage will be maximized, but also the transportation sector will be greener and economical. Furthermore, they can participate in the local electricity market to submit offers/bids that maximize their collective profit as they can exert influence in the local market. Along with offering valuable network services, the LEM also provides significant financial advantages for the partakers, including grid operators, aggregators, and users. Ref. [3] presents a LEM for community load and EVs to

minimize the impact of intermittent renewable generation while enabling prosumers as reserve providers. A game theory based LEM is proposed in [4] to achieve optimal microgrid energy management while considering multiple market operations. However, energy trading is neither economically optimal nor risk-averse. Ref. [5] proposes energy trading for EV participation in the multi-market system to minimize the charging costs but neglects the profit maximization objectives.

Based on the assessment of relevant literature in the area of the local energy market using electric vehicles, the majority of the papers do not consider the conflicting objectives of all market participants (producers and consumers). This work proposes a nonlinear optimized clearing-by-bid trading mechanism that provides producer agents with a maximum profit range while minimizing the cost of energy procurement by consumer agents. A case study of real data from Auckland is used to demonstrate the feasibility of the proposed model.

The salient features of this article can be summed up as follows:

1) A nature-based optimization framework for local energy trading, incorporating an aggregator for integration of LEM with the wholesale market.
2) A market clearing-by-bid energy trading model for the community comprising PV and EVs.
3) A case study using actual data to assess the impact of LEM participation and aggregator tariffs.

PROPOSED FRAMEWORK

To maintain self-sufficiency in a local area, it is assumed that end-users in the local area can trade energy with the wholesale market through an aggregator. Fig. 1 shows the proposed model structure consisting of LEM to trade energy within end-users (agents). An aggregator is considered to enable integration with the wholesale energy market. The LEM comprises two agent types: consumers (i.e., EV users) and producers (i.e., consumers having PV generation). The producers with PV generation self-consume the produced energy and feed the excess to the grid through an aggregator. The market structure is hierarchical, with the trading initiated in LEM and settled there. The remaining energy is forwarded to wholesale markets. Different tariffs imposed by the aggregator are analysed in this paper.

The LEM bidding problem is formulated as an optimization problem to maximize the agents' profits. At the same time, maximum energy is being transacted in the LEM. The EMS communicates with the different microcontrollers attached to the system components (PV system, EV charger, and converters) and coordinates the LEM.

To reach the optimal operation condition, the EMS will consider electricity market dynamics based on the following factors: forecasted PV output, electricity prices and EV demand, metrics of EVs available, trading incentives and cost. The EMS manages the charging/discharging of EVs

through the charging controller in the chargers. It acts as a coordinator for all EVs for energy arbitrage.
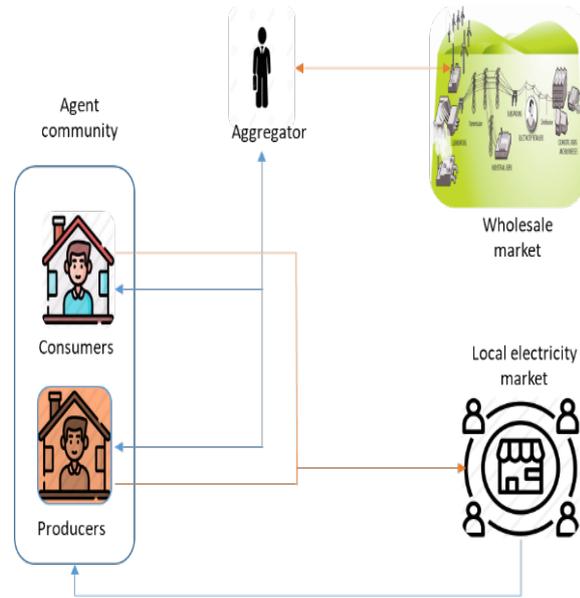
Fig. 1: Model of the proposed framework

FORECASTING

This section presents the Autoregressive Integrated Moving Average (ARIMA) based forecasting of PV output and Recurrent Neural Network (RNN) based forecasting of electricity prices, used as input signals.

PV Output Forecasting

The PV output forecasting is Seasonal ARIMA with a temporal resolution of 1 hour. The yearly irradiation and temperature data were taken from the National Institute of Water and Atmosphere (NIWA) for the city of Auckland, New Zealand [6]. Since the solar irradiation data shows seasonality, the ARIMA model is extended to Seasonal ARIMA (SARIMA).
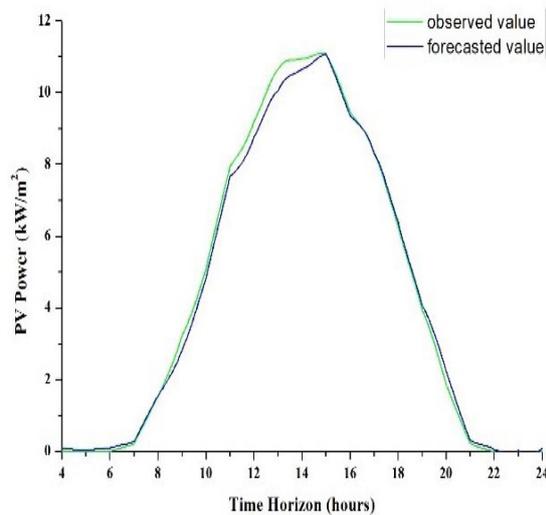
Fig. 2: Profile of observed and forecasted PV power

The SARIMA model chosen is (p = 3, d = 0, q = 2) x (P = 1, D = 0, Q = 1)s=24. The R^2 and root mean square error (RMSE) amount to 0.938 and 62 W/m^2, respectively. Therefore, the selected model is suitable for forecasting. Fig. 2 shows a comparison of a daily profile of forecasted PV power and observed PV power.

The generated PV output is computed from the forecasted irradiation from (1) [7].

$$P_{PV_t} = \eta A_{PV} G_F \left(1 - \frac{T_C - 25}{200}\right) \qquad (1)$$

where, η = efficiency of PV module,

A_{PV} = PV module's surface area (m^2)

G_F = forecasted solar irradiation (kW/m^2)

T_C = panels' operating temperature (°C)

Electricity Price Forecasting

A recurrent neural network-based LSTM (long short term memory) model is used for forecasting wholesale electricity prices. A one-year historical dataset is obtained from the NZ Wholesale Information Trading System [8]. The test-train split chosen is 90:10. The LSTM layer is chosen to have 200 hidden units and trained using *adam* solver in Matlab. The R^2 and MAPE (Mean Absolute Percentage Error) are found to be 0.955 and 7.85%, respectively. Fig. 3 shows the segment forecasting profile of electricity buying price for one month period. More implementation details can be found in [9].
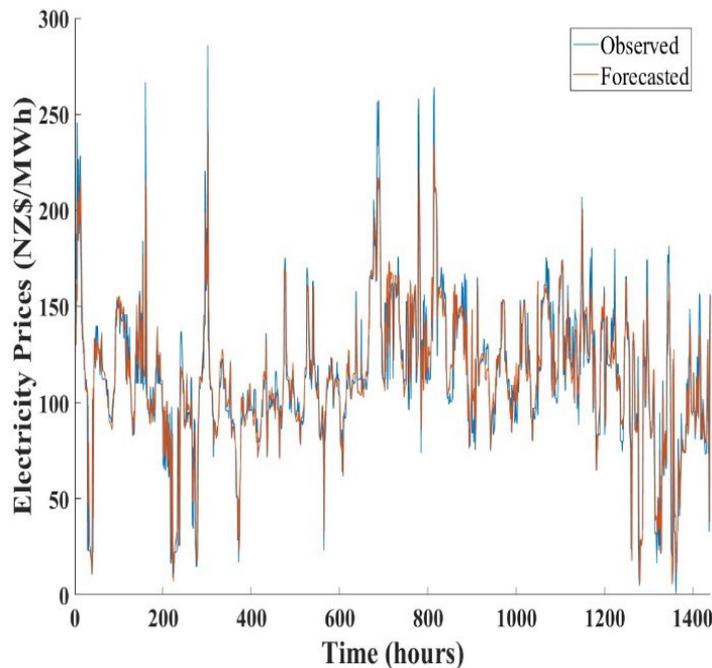
Fig. 3: Profile of observed and forecasted electricity price

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EV Charging Demand

The community parking lots are assumed to cater to primarily residential EV users. Hence, the parking occupancy is related to non-working hours from 5.00 pm to 9.00 am the next day. The distribution of EV arrival and departure times are assumed to be normally distributed based on (2).

$$f(t_i) = \frac{1}{\sigma_t\sqrt{2\pi}} e^{-\left[\frac{(t_i - \mu_t)^2}{2\sigma_t^2}\right]} \qquad t > 0 \tag{2}$$

where $i = \{1, 2, \dots N\}$ represents *i-th* EV, σ_t and μ_t are mean and standard deviation, respectively. The EV distribution characteristics are adopted from [10].

The EV fleet composition in Auckland comprises many different types of EVs with variations in the battery capacity from 9 to 60 kWh [11]. In the literature, the battery energy content or SoC is often represented using uniform [12], normal [13] and log-normal [14] probability functions. Here, a normal distribution function with maximum and minimum SoC limits of 0.9 and 0.1, respectively, is assumed. The characteristic data of different types of EVs are presented in Table I.

TABLE I EV CHARACTERISTICS DATA

Model	Battery capacity [kWh]	Max charging power [kW]
Mitsubishi Outlander	13.8	3.7
Hyundai Ioniq	38.3	7.2
Tesla Model 3	55	7.4
Toyota Prius	8.8	3.3
Nissan Leaf	40	3.6

SYSTEM MODELLING

The LEM trading is formulated as a bi-level optimization problem. Readers can refer to [15] for modelling EVs and PV.

Eqs. (3) and (4) represent the cost function for consumer agents and producer agents, respectively.

$$C(i) = \sum_j c^p . E_{j,i} + c^{agg} . E_{buy_{grid,i}} \tag{3}$$

where i = number of consumer agents, j = number of producer agents, c^p is LEM clearing price, $E_{j,i}$ is energy sold in LEM, c^{agg} is the aggregator rate, $E_{buy_{grid,i}}$ is energy bought from the grid.

$$P(j) = \sum_i c(p) . E_{j,i} + c^{FIT} . E_{sell_{j,grid}} - c^m . E_{PV} \tag{4}$$

where c^m is the marginal cost, $E_{sell_{j,grid}}$ is energy sold to the grid.

The optimization problem is modelled as LEM energy trading, in which LEM clearing price is determined by equating demand with supply. All the participating agents communicate their

requirements in the form of bids comprising of quantity and price. The consumer bid is constrained by limits [0, E^i_{max} (maximum energy demand)].

While the producer bid is constrained by $[E^j_{max} - E_{PV}, 0]$ i.e., between excess energy after PV self-consumption and 0. The authors assume that producers self-consume the PV first. At the same time, the excess of energy can be sold either in the LEM or injected to the grid at the feed-in tariff.

The bid price is restricted between the bounds of wholesale electricity price and feed-in tariff to make the LEM feasible. Based on the outcome of the bidding in the previous trading interval (taken as a 1 hr segment), the market participants update their bids in the upcoming trading interval to increase their chances of bid acceptance.

The optimization objective is to increase the overall mean profits of the LEM while, also maximizing the agents' individual profits. Eq (5) depicts the objective function to optimize.

$$max \sum_j \frac{P_j}{N_p} - \sum_i \frac{C_i}{N_c} \qquad (5)$$

Where C_i and P_j are conflicting objectives as agents want to achieve the best result for their own. For detailed mathematical formulation of the problem readers can refer to [1], [16].
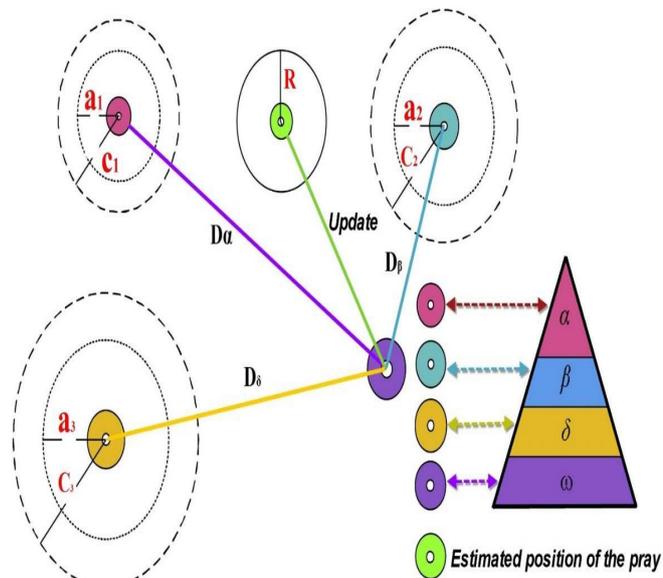
Fig. 4: Principle of grey wolves hunting

Grey Wolf Optimization

This section describes in detail the GWO algorithm as an efficient evolutionary method with many merits, such as not being trapped into local optimum [17]. The procedure of the GWO algorithm can be briefly stated as below.

This algorithm was presented for the first time as a hierarchical optimization technique in [17] by Mirjalili, et al., and it is developed using the strategies taken by a wolf pack for hunting. In general, a wolf pack has four groups including the leader group shown by α as the top ones showing

the best solutions. It is noteworthy that other groups of best solution in a hierarchical manner include β, δ, ω, as the second to the fourth groups indicating other fitness solutions in order. The omega group is located at the lowest position and they should submit to the three other groups. A significant feature of a wolf pack, the group hunting is described in Fig. 4 [18] and is summarized as follows:

- Going after the quarry and getting close to it
- Sieging and pestering the quarry till the time it stops running
- Attacking the quarry

By using the following equations, any member of the wolf pack would be able to change its position within the area surrounding the quarry. These equations indicate the sieging trend in a wolf pack.

$$D = \left| C.X_{p,k} - X_k \right| \tag{6}$$

$$X_{k+1} = X_{p,k} - A.D \tag{7}$$

where the vector of coefficients is denoted by A and C and determined utilizing (6) and (7). Besides, k shows the current iteration, and the location vectors of the quarry and a grey wolf are expressed by $X_{p,k}$ and X_k, respectively.

$$A = (2r_1 - 1).a \tag{8}$$

$$C = 2r_2 \tag{9}$$

The variables r_1 and r_2 in (8) and (9) show vectors of random values mapped in the interval [0 1]. Moreover, α declines from 2 to 0 during the iterations. It is noteworthy that group α leads the hunting activity, while the second and the third level groups, i.e. β and δ take part in the hunting, randomly. For the sake of better modeling, the first three groups, i.e. α, β and δ are considered as pioneers in terms of knowing the possible position of the quarry. Accordingly, the solutions obtained from these three groups are kept and other search agents will be made to renew their locations with respect to the best solution using the relationships given in (10)-(14).

$$D_\alpha = \left| C_1.X_{\alpha,k} - X_k \right| \tag{10}$$

$$D_\beta = \left| C_2.X_{\beta,k} - X_k \right| \tag{11}$$

$$D_\delta = \left| C_3.X_{\delta,k} - X_k \right| \tag{12}$$

$$X_1 = X_\alpha - A_1.D_\alpha$$
$$X_2 = X_\beta - A_2.D_\beta$$
$$X_3 = X_\delta - A_3.D_\delta \tag{13}$$

$$X_{k+1} = \frac{1}{3}(X_1 + X_2 + X_3) \tag{14}$$

The variable A in (8) indicates the coefficient of decisive weights pertaining to the first three groups and slowly decreases. The overall process is explained in Fig. 5 [19].

In brief, the mechanism of the GWO method can be stated as below:

- Determining the size of the population
- Employing the seeking factors to siege the quarry in the top and bottom of the space around the quarry
- Assessing the compatibility value of each individual solution, showing the distance of each seeking agent from the quarry. Three superior groups of wolves are determined according to the fitness as *a*, *b*, and *g*. To get the quarry utilizing (9)-(12), the hunting performance of the wolves groups are reconsidered.
- Renewing the position and state of each grey wolf based on (13) and (14).
- Redoing Steps 3 to 4 until the quarry is hunted.
- Check if the stop condition is satisfied.
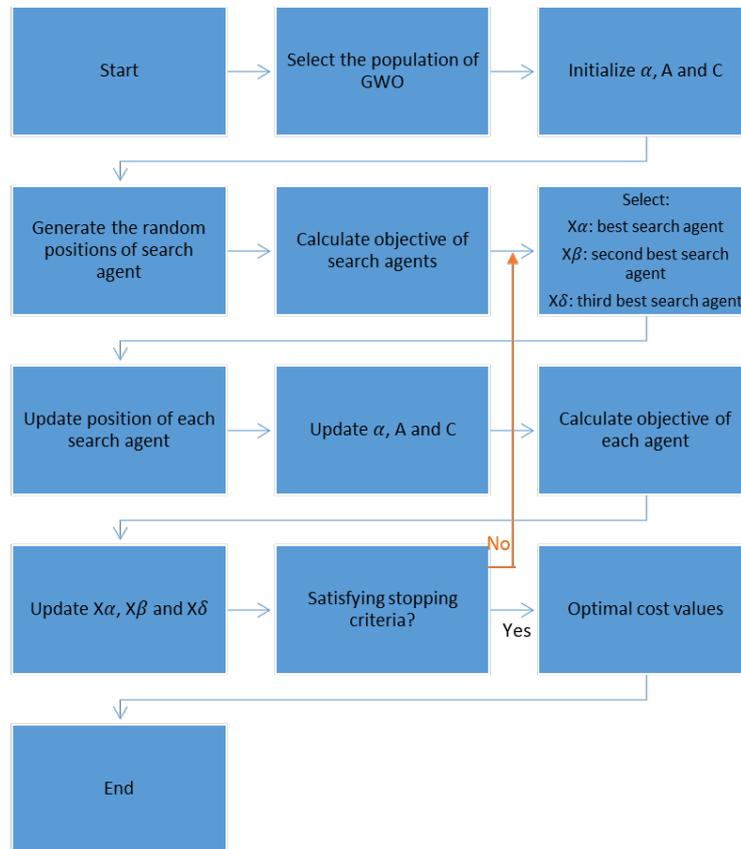
Fig. 5: Flowchart of the GWO algorithm

RESULTS

In this section, the results of the simulations are presented. The optimization problem is solved using CPLEX solver on neos-server. The aggregator tariff variation impact on LEM is analyzed by considering the price variation in aggregator tariff from 0.16 NZD/kWh to 0.41 NZD/kWh. The case study comprises of six agents, in which 3 are consumers and 3 are producers (consumers with PV generation). The value chosen for fixed Feed-in Tariff (FIT) is 0.08 NZ$/kWh [20].

The impact of variation of aggregator fees with and without LEM on operating cost is shown in Table II. The cost or profits of agents (consumers and producers) are also shown in different scenarios. The negative values represent profit. All the cost are in NZD with total cost of system shown in the last column, the lower the better. It is evident from results that application of LEM drastically reduces the total operating cost of the system in the range of 29-39%. With the increase in the aggregator tariffs, the producer agents obtain more profits by participating in LEM. In this scenario, the producers' agents prefer selling energy to consumers instead of selling to grid at FIT. In one particular case of producer agent selling at loss (p2, LEM + 10% Cagg), participation in the LEM cannot outweigh the fee variations experimented with the aggregator. Nonetheless, a realistic scenario with presence of more producers' agents selling energy will outweigh the aggregator cost variations.

TABLE II   COMPARISON OF OPERATING COST (NZD)

	Consumers			Producers			
	i1	*i2*	*i3*	*p1*	*p2*	*p3*	Total
No LEM + 10% Cagg	5.19	7.43	5.15	0	0	0	17.78
LEM + 10% Cagg	5.01	6.96	4.97	-4.3	4.2	-4.3	12.49
No LEM + 15% Cagg	4.78	6.23	4.77	0	0	0	15.78
LEM + 15% Cagg	5.16	7.51	5.14	-3.15	-0.81	-3.17	10.69

CONCLUSIONS AND FUTURE WORK

LEMs can unlock several benefits for end-users, utilities, and the system as a whole. However, the conflicting objectives between diverse participants make it difficult to model the interactions of LEM. This work presents a framework for trading between agents in an LEM and the wholesale market through an aggregator. The uncertainty in PV and wholesale electricity price is reduced through forecasting techniques. The grey wolf optimization algorithm is used for maximizing agents' profits without privacy concerns. The LEM is shown to improve agents profits even with different aggregator's tariff values. The variation of LEM clearing price with respect to demand or excess PV generation is also to be studied as an extension of this research. Also, constraints on network operations, incorporation of storage unit, presence of uncertainty in renewable generation, and the transaction validation of LEM by a distribution network operator (DSO) are things to be considered in future work.

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Chapter 4: Manuscript 3 – Workplace TEMS for EV-PV System

This manuscript introduces a Transactive Energy Management System (TEMS) designed for commercial parking lots featuring both EV charging and rooftop photovoltaic (PV) systems. The TEMS is initially optimized to balance charging demand with available supply, considering factors such as battery degradation costs and the levelized cost of energy for PV. In a subsequent phase, the TEMS of each parking lot communicates energy requirements and surplus energy to a local trading agent, initiating a transactive energy transaction mechanism. This mechanism employs a double-sided auction bidding approach that offers price flexibility based on the valuation of energy requirements within the parking lots. The TEMS is optimized to minimize the system cost. Further, the uncertainties associated with PV generation and electricity prices are modelled using discrete probability distribution and their effect on TEMS is analysed. It is also observed that due to the comparatively high marginal cost of PV generation in contrast to off-peak utility tariffs, charging costs increase with extensive PV consumption.

Transactive Energy Management of PV based EV integrated Parking Lots

Asaad Mohammad, Ramon Zamora, *Member, IEEE*, and Tek-Tjing Lie, *Senior Member, IEEE*

Abstract— Electric Vehicles (EVs) are a viable alternative for a sustainable mode of transportation. A huge penetration of EVs in future will lead to increasing demand in commercial parking lots equipped with the charging system. Hence, this research area is being pursued meaningfully in recent years. This paper proposes a transactive Energy Management System (EMS) for commercial parking lots equipped with EV charging system and rooftop PV system. Initially, the EMS is optimized with the objective of balancing charging demand with supply. To make the EMS more realistic, factors such as battery degradation cost and Photovoltaic (PV) Levelized cost of energy are considered. At the later stage, the EMS of each parking lot communicates the energy requirement and excess energy to the local trading agent to initiate the proposed transactive energy transaction mechanism. The double-sided auction bidding mechanism is price flexible and based on the valuation of the energy requirement of parking lots. For a system with 6 parking lots and 25 EVs in each, the proposed scheme results in cost savings in the range of 2% to 7% for different cases of fixed and variable feed-in tariff. The uncertainty analysis shows that the cost savings vary from a minimum of 2.41% to maximum 12.09% with an average of 6.11%. The case studies demonstrate the potential economic benefit of the proposed scheme.

Index Terms- electric vehicles, energy management system, EV parking lot, power markets, optimization

NOMENCLATURE

Variables and indices are symbolized by italics, while parameters are represented by regular letters.

Sets and Indices

t	Time period, from 1 to T hours
i	Electric vehicles, from 1 to N
p	Parking lots, from 1 to P
p_{sell}	Parking lots selling excess energy
p_{buy}	Parking lots buying excess energy

Parameters

P_{PV}^{Max}	Maximum PV power [kW]
η_{inv}	DC-AC inverter efficiency [%]
η_{DC-DC}	DC-DC converter efficiency [%]
η_{chrg}	EV charging efficiency [%]
η_{dschrg}	EV discharging efficiency [%]
C_{deg}	Battery degradation cost [NZ$/kWh]
C_{PV}	PV levelized cost of energy [NZ$/kWh]
C_{FIT}	Feed-in tariff cost [NZ$/kWh]

SoC_{Min}	Minimum Battery State of Charge limit [%]
SoC_{Max}	Maximum Battery State of Charge limit [%]
$P_{chrg_{i,t}}^{Max}$ $P_{dschrg_{i,t}}^{Max}$	Maximum charging/discharging power of ith EV at time t [kW]
$SoC_{i,p}^{Arrv}$	Arrival SoC of ith EV in pth parking lot [%]
$SoC_{i,p}^{Dept}$	Departure SoC of ith EV in pth parking lot [%]
$T_{i,p}^{Arrv}$	Arrival time of ith EV in pth parking lot [hr]
$T_{i,p}^{Dept}$	Departure time of ith EV in pth parking lot [hr]
P_{PV_t}	PV output power [kW]
C_{elec_t}	Wholesale electricity buying price [NZ$/kWh]
BC_i	Battery capacity of the ith EV [kWh]
σ_p	Choice factor of pth parking lot

Variables

C_{tot}	Total charging/discharging cost [NZ$]
$P_{EV_{i,t,p}}$	Total power transfer to/from ith EV in pth parking lot at time t [kW]
$SoC_{i,t,p}$	SoC of ith EV in pth parking lot at time t [%]
$P_{v2g_{i,t,p}}$	Power transfer to grid from ith EV in pth parking lot at time t [kW]
$P_{g2v_{i,t,p}}$	Power transfer from grid to ith EV in pth parking lot at time t [kW]
$P_{PV2EV_{i,t,p}}$	Power transfer from PV to ith EV in pth parking lot at time t [kW]
$P_{PV2G_{t,p}}$	Power transfer from PV in pth parking lot to grid at time t [kW]
$E_{Exc_{t,p}}$	Excess energy of pth parking lot at time t [kWh]
$E_{Req_{t,p}}$	Required energy of pth parking lot at time t [kWh]
E_{tot}^{PV}	Total PV energy consumption [kWh]
$C_{bid_{t,p}}$	Bidding price of pth parking lot at time t [NZ$]
$E_{val_{t,p}}$	Energy valuation of the pth parking lot at time t [kWh]
$E_{t,p}^{max}$	Max energy allowed for trading for pth parking lot at time t [kW]

I. INTRODUCTION

The issues like global warming, depleting fossil fuel reserves and greenhouse gas (GHG) emissions need dire attention for ensuring a sustainable future. Because the transportation sector is one of the largest contributors to the rising harmful emissions, the electrification of transportation is seen as a promising solution for this problem. Electric Vehicles (EVs) provide an emission-free alternative while reducing dependency on petroleum imports for transportation purpose, thereby increasing energy security. Due to difficulty in installing EV charging set up in many homeowners' garage/parking space, commercial parking space can be leveraged for EV charging purposes as many EVs spend a considerable amount of time in parked conditions [1].

For controlling many distributed energy resources (e.g., EVs), innovative decentralized control methods like Transactive Energy (TE) control is necessary. Compared to centralized control methods, the TE methods are appealing to EV users as the users are an integral part of the decision process [2]. Due to the limited information exchange (price and amount of energy traded) in the TE trading, EV users are independent without compromising their privacy. "The intent of transactive control is to reach equilibriums by standardizing a scalable, distributed mechanism via exchanging information about generation, consumption, constraints, and responsive assets over dynamic, real-time forecasting periods, using economic incentive signalling, and thus solving complex power system problems"[3]. Therefore, in the TE control, interactions between entities are managed instead of actions. Along with offering useful network services, TE method also offers significant financial advantages for the partakers including grid operator, aggregators, and users. Ref. [4] analyzes peak load management of commercial buildings using parking lots' EVs without a focus on energy trading. Ref. [5] presents a TE management of community load and EVs to minimize the impact of intermittent renewable generation and to regulate the voltage. Ref. [6] presents a TE based trading approach for EVs considering bid submission by individual users, to minimize the charging cost. Refs. [7] and [8] propose peer to peer (P2P) trading model to minimize system cost and increase renewable self-sufficiency while neglecting the user preferences. Ref. [8] model also requires sharing of consumer's energy consumption, thereby raising privacy concerns. Similarly, authors in [9] propose a game theory P2P trading model for renewable sources integrated microgrid to minimize the system operation cost. However, no economic or social rationale is provided for the chosen bidding strategy. The authors in [10], [11] propose multi-agent transactive trading mechanism to maximize cost savings of consumers and minimize the overloading of distribution transformers. However, the transactive model is not price bidding flexible. Ref. [12] presents an energy valuation based double-sided trading mechanism is proposed between microgrids to reduce reliance on utility grid. However, bidding price is without constraints which can lead to inefficient market equilibrium i.e., bid price may be higher or lower than the feed-in tariff or utility price. Ref. [13] proposes a game theory-based multiagent energy market trading to achieve optimal microgrid energy management while considering the day-ahead, hour-ahead and real-time market operation. However, energy trading is neither socially optimal nor risk-averse.

Based on the assessment of relevant literature in the area of transactive energy trading using Electric Vehicles, majority of the papers do not either consider market participant preferences or requires sharing of data thereby raising privacy concerns. Also, none of the papers offer flexibility in terms of bids value to the market participants to the best of knowledge of authors. This article proposes a bidding price flexible transactive trading mechanism which provides EV aggregators with wider bidding price range to increase the chances of procuring required energy need. A case study of real data from Auckland is used to demonstrate the feasibility of our model.

The salient features of this article can be summed up as following:

1. A double-sided auction based transactive energy trading model for the PV based workplace EV charging station has been proposed.

2. A novel flexible-price bidding strategy is formulated to alleviate the limitations associated with the pricing bound.

3. The EV charge scheduling problem is formulated while considering uncertainties as Mixed Integer based optimization model to minimize the charging cost.

II. PROPOSED FRAMEWORK

A multiple parking lot system is considered with each parking lot acting as an aggregator of EVs. The EMS of each parking lot fulfils its charging demand with the power supplied from the PV system and grid. Figure 1 shows the proposed system with six parking lots. Abundant charging points are assumed to be available using the modular converter [14] and charging power is assumed to be constant at rated value. The EMS communicates with the different microcontrollers attached to the system components (PV system, EV charger, and converters).

To reach the optimal operation condition, the EMS will consider electricity market dynamics based on the following factors: forecasted PV output, electricity prices and EV demand, metrics of EVs parked, trading incentives and cost.

The EMS manages the charging/discharging of EVs through the charging controller in the chargers and acts as a coordinator for all EVs for energy arbitrage. The aggregator will make the decision to charge/discharge individual EVs based on the initial state of charge (SoC), target SoC, parking duration, and charging cost.

The system operation can be broken down in three stages:

- In the first stage, EMS will forecast the PV output and electricity prices.

- In the second stage, EMS will balance the EV load demand with the supply (PV and grid).

- In the third stage, the aggregator will participate in transactive energy trading to minimize the system cost.

The auction mechanism is supervised by the local trading agent through which buyers and sellers submit their bid for energy transaction.
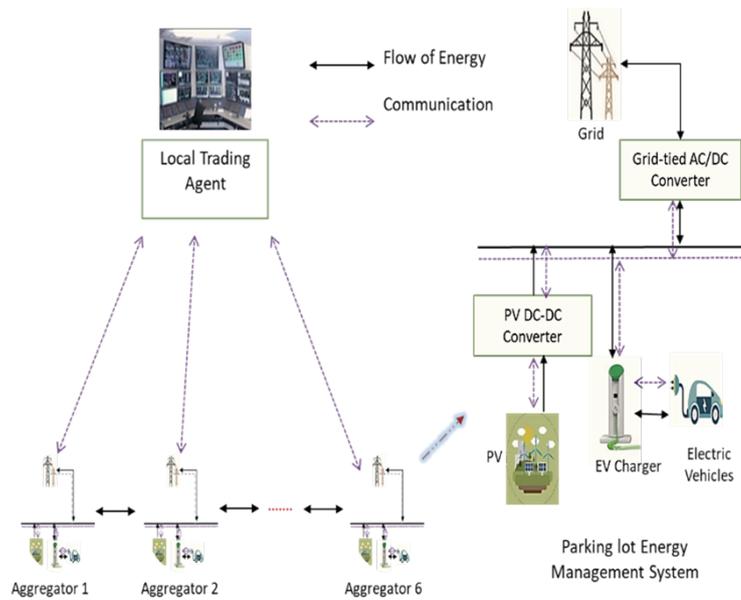
Figure 1: Model of the proposed system

The trading process starts with EMS present in aggregator (parking lots) estimating the overall energy demand and PV energy generation for each hour. After which, the EMS balances out the supply and demand. The EMS also estimates the excess amount of energy available and communicates this value to the local trading agent, who broadcasts the average available excess energy. The buyers requiring energy do a private valuation of their energy requirement and place their bids to the local trading agent. Similarly, sellers also submit their bids for selling excess energy based on their private valuation. Upon collecting all the bids, the local trading agent deploys an auction method of double-side nature for clearing market and allocating energy. Figure 2 shows the flowchart of the proposed system.
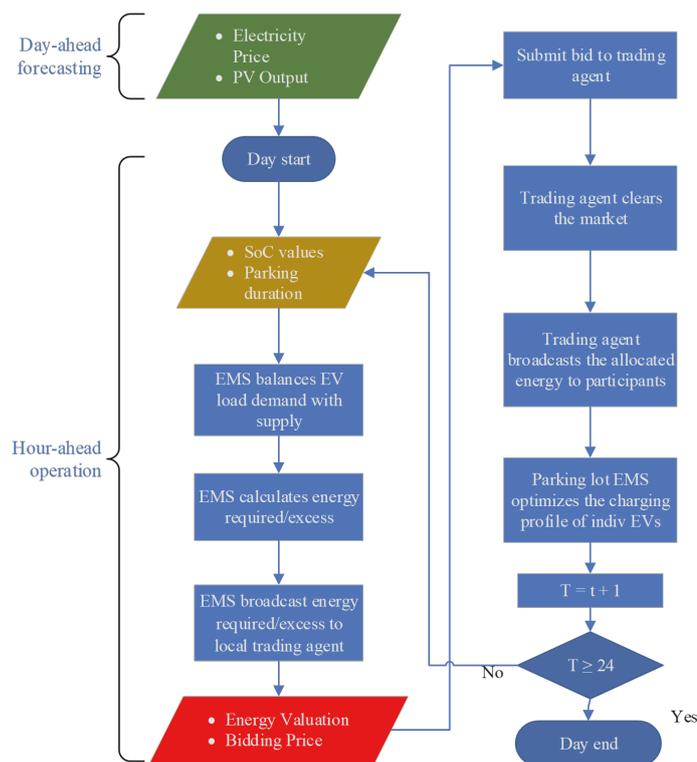
Figure 2: Flowchart of the system

III.   FORECASTING

This section presents the Autoregressive Integrated Moving Average (ARIMA) based forecasting of PV output and Electricity prices, which are used as input signals.

A. PV Output Forecasting

The PV output forecasting is generally done through either physical models or statistical models, in which the statistical models are more apt for intraday forecasting. For low temporal resolutions, ARIMA models are most accurate compared to other statistical methods [15]. Hence ARIMA was selected for this work with the temporal resolution of 1 hr. The yearly irradiation and temperature data were taken from the National Institute of Water and Atmosphere's (NIWA) for the city of Auckland, New Zealand [16]. The ARIMA model is comprised of two parts, the Autoregressive component of class p ($AR(p)$) and the Moving Average component of class q ($MA(q)$). To make the series stationary, differencing is applied in Integrated component of class d ($I(d)$). Since the solar irradiation data shows seasonality, the ARIMA model is extended to Seasonal-ARIMA (SARIMA). The SARIMA process can be abbreviated as (p, d, q) x $(P, D, Q)_s$. The obtained parameters of the chosen SARIMA ($p = 3, d = 0, q = 2$) x ($P = 1, D = 0, Q = 1)_{s=24}$ are described in Table I.

TABLE I
SARIMA MODEL PARAMETERS

Parameters	Value (PV Forecasting)
AR (2)	0.813
AR (3)	-0.813
MA (1)	-1.051
MA (2)	-0.51
Seasonal AR (1)	0.995
Seasonal MA (1)	0.889

For evaluation of the adopted SARIMA model, R^2 and root mean square error (RMSE) are examined, which amount to 0.938 and 62 W/m^2, respectively. Therefore, the selected model is suitable for forecasting.

Figure 3 shows a comparison of a daily profile of forecasted PV power and observed PV power. Monocrystalline PV panels with the efficiency of 19% are considered here. The generated PV output is computed from the forecasted irradiation from (1) [17].
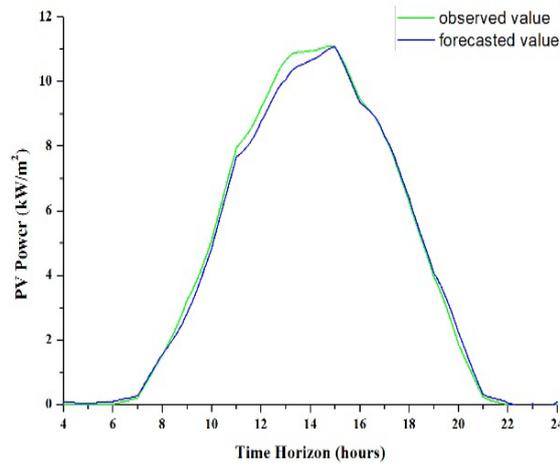
Figure 3: Single day profile of observed and forecasted PV power.

$$P_{PV_t} = \eta A_{PV} G_F \left(1 - \frac{T_C - 25}{200}\right)$$ (1)

where, η = efficiency of PV module,

A_{PV} = PV module's surface area (m^2)

G_F = forecasted solar irradiation (kW/m^2)

T_C = panels' operating temperature (°C).

B. Electricity Price Forecasting
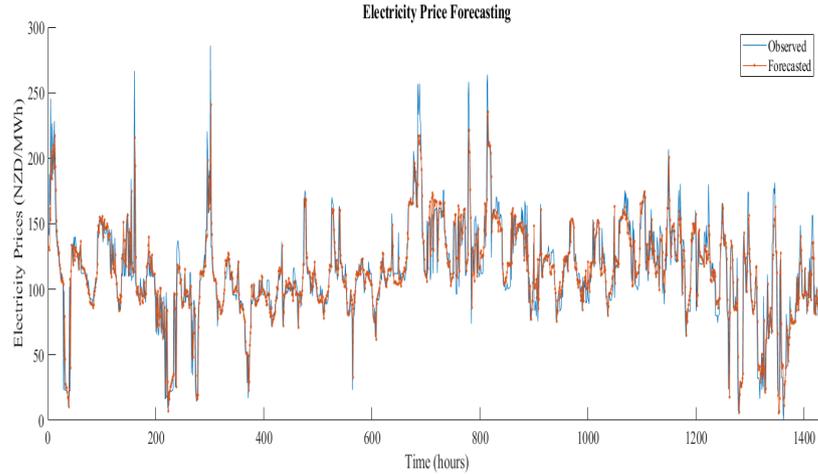
Figure 4: Profile of forecasted and observed electricity buying price.

A deep recurrent neural network based LSTM (long short-term memory) model is used for forecasting of the electricity buying price based on the 1 year historical data obtained from the NZ Wholesale Information Trading System [18]. The model was trained on first 90% of the series and rest 10% was used for testing. The LSTM layer was chosen to have 200 hidden units. The model was trained using *adam* solver for 250 epochs in Matlab. Readers can refer to [19] for implementation details on deep recurrent neural network based LSTM forecasting model. The R^2 and MAE% (Mean Absolute Error %) were found out to be 0.955 and 7.85% respectively, which justifies the aptness of the chosen model for forecasting. Figure 4 shows the segment forecasting profile of electricity buying price for a month period.

C. EV Charging Demand

The parking lots are assumed to cater to mostly workplace EV users. Hence, the parking occupancy is related to working hours from 9.00 am to 5.00 pm. The distribution of EV arrival and departure times are assumed to be normally distributed based on (2).

$$f(t_i) = \frac{1}{\sigma_t\sqrt{2\pi}} e^{-\left[\frac{(t_i-\mu_t)^2}{2\sigma_t^2}\right]} \qquad t > 0 \tag{2}$$

where $i = \{1,2,...N\}$ represents ith EV, σ_t and μ_t are mean and standard deviation respectively. Table II shows the EV distribution characteristics adopted from [20].

TABLE II
EV PROBABILITY DISTRIBUTION PARAMETERS

	Initial SoC	Departure SoC	Arrival	Departure
Mean (h)	0.5	0.6	9 am	5 pm
St. Deviation (h)	0.25	0.25	3	3

The EV fleet composition in Auckland is comprised of many different types of EVs with variation in the battery capacity from 9 to 60 kWh [21]. Ref. [22] shows that the workplace charging only extends the range of EVs and not charge them completely. In the literature, the battery energy content or SoC is often represented using uniform [23], normal [24] and log-normal [25] probability functions. Here, a normal distribution function with maximum and minimum SoC limit to be 0.9 and 0.1, respectively, is assumed.

Table III shows the EV characteristic data.

TABLE III
EV CHARACTERISTIC PARAMETERS

Model	Battery capacity [kWh]	Max charging power [kW]	No per parking lot
Mitsubishi Outlander	13.8	3.7	3
Hyundai Ioniq	38.3	7.2	3
Tesla Model 3	55	7.4	3
Toyota Prius	8.8	3.3	6
Nissan Leaf	40	3.6	10

IV. SYSTEM MODELLING

The EV charging process is non-linear in nature. However, it is generally approximated as a linear process. This work also considers EV charging as linear. The problem is modelled as mix integer nonlinear programming (MINLP) problem which is further linearized in general algebraic modelling system. The problem formulation is generic and can be extended to a large scale.

A. Constraint Design

1) EV Constraints:

The charging and discharging power of individual EV is bounded by power limits:

$$P_{g2v_{i,t,p}} + P_{PV2EV_{i,t,p}} \leq P^{Max}_{chrg_{i,t}} \tag{3}$$

$$P_{v2g_{i,t,p}} \leq P^{Max}_{dschrg_{i,t}} \tag{4}$$

The EV is restricted to either charging or discharging process at a time based on (5):

$$u \times \left(P_{g2v_{i,t,p}} + P_{PV2EV_{i,t,p}}\right) + (1-u) \times P_{v2g_{i,t,p}} = 0 \tag{5}$$

where $u = \{0,1\}$ is a binary variable.

EVs receive less power than the available power at the charging point due to system losses. The charging/discharging efficiency of EVs is taken as 90% [26]. The power transferred to EV is given by (6).

$$P_{EV_{i,t,p}} = \eta_{chrg} * \left(P_{g2v_{i,t,p}} + P_{PV2EV_{i,t,p}}\right) - \left(\frac{P_{v2g_{i,t,p}}}{\eta_{dschrg}}\right) \tag{6}$$

The SoC of EVs can be calculated from (7), where EV users decide their departure SoC.

$$SoC_{i,t,p} = \begin{cases} 0 & for\ t < T^{Arrv}_{i,p} \\ SoC^{Arrv}_{i,p} & for\ t = T^{Arrv}_{i,p} \\ SoC_{i,t-1,p} + \frac{P_{EV_{i,t,p}}}{BC_i} * \Delta t & for\ T^{Arrv}_{i,p} < t < T^{Dept}_{i,p} \\ SoC^{Dept}_{i,p} & for\ t \geq T^{Dept}_{i,p} \end{cases} \tag{7}$$

$$SoC_{Min} \leq SoC_{i,t,p} \leq SoC_{Max} \tag{8}$$

$$\begin{cases} P_{v2g_{i,t,p}} = 0 \\ P_{g2v_{i,t,p}} = 0 & for\ t < T^{Arrv}_{i,p}\ or\ T^{Dept}_{i,p} < t \\ P_{PV2EV_{i,t,p}} = 0 \end{cases} \tag{9}$$

Eq. (8) specifies the constraint to preserve battery life and protect them from deep discharges and overcharges. When EVs are disconnected from the parking lot charging system, the constraints specified by (9) are applied.

2) PV System Constraints:

The parking lot has a PV system with a rated capacity of 10 kW$_p$. The efficiency of both the converter and inverter of the PV system is selected as 98% [27] [28]. To allow the EMS to curtail excess PV power above the rated capacity, (10) is used.

$$\frac{\sum_{i=1}^{N} P_{PV2EV_{i,t,p}}}{\eta_{DC-DC}} + \frac{P_{PV2G_{t,p}}}{\eta_{DC-DC} * \eta_{inv}} \leq P_{PV_t} \leq P^{Max}_{PV} \tag{10}$$

B. Objective Function

As high cost is a significant barrier for the consumers to adopt EVs, the optimization problem is formulated to minimize the associated costs with EV. Further to make the proposed system

more sustainable in nature, the problem maximizes the PV self-consumption. Eq. (11) shows the objective functions and decision variables.

$$Min(C_{tot}) = Min\left\{\left(\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(P_{g2v_{i,t,p}} * C_{\text{elec}_t} + P_{v2g_{i,t,p}} * C_{\text{deg}} + \left(P_{PV2EV_{i,t,p}} + P_{PV2G_{t,p}}\right) * C_{\text{PV}} - \left(P_{v2g_{i,t,p}} + P_{PV2G_{t,p}}\right) * C_{\text{FIT}}\right)\right) * \Delta t\right\} \qquad (11)$$

The first term in (11) denotes the cost of buying electricity from the utility. The battery degradation due to participation in V2G is represented by the second term. The third term represents the marginal cost of PV power generated, i.e. LCOE of PV system. The power sold back to the grid is characterized by the fourth term. Eq. (12) denotes the total PV self-consumption of the parking lots which is comprised of two terms: PV energy sold to grid and PV energy used to charge EVs.

$$E_{tot}^{PV} = \left\{\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(P_{PV2EV_{i,t,p}} + P_{PV2G_{t,p}}\right) * \Delta t\right\} \qquad (12)$$

V. ENERGY TRADING MODEL

The EMS monitors the energy status of the parking lot and commences the process of energy trading by calculating the excess energy/required energy available for selling/buying. This value is communicated to the local trading agent which is further conveyed to all parking lots interested in buying or selling energy. Based on the amount of excess energy available, the buyers can make a valuation of their own energy requirement and formulate their bids for participating in energy trading. The local trading agent employs a double-sided auction mechanism upon bid submission from all the buyers and sellers. Eqs. (13) and (14) represent the amount of energy to be traded amongst the parking lots.

$$E_{Req_{t,p}} = \sum_{i=1}^{N} P_{g2v_{i,t,p}} * \Delta t \qquad p \, \epsilon \, p_{buy} \qquad (13)$$

$$E_{Exc_{t,p}} = \sum_{i=1}^{N}\left(P_{v2g_{i,t,p}} + P_{PV2G_{t,p}}\right) * \Delta t \qquad p \, \epsilon \, p_{sell} \qquad (14)$$

Eq. (15) constraints the number of parking lots participating in energy trading. The average excess energy available for selling per parking lot is represented by (16).

$$p_{sell} + p_{buy} = P \qquad (15)$$

$$E_{Exc_{t,p}}^{avg} = \frac{E_{Exc_{t,p}}}{p_{buy}} \qquad (16)$$

Eq. (17) represents the energy valuation of each parking lots aiming to buy energy. Based on this valuation, each buyer submits its bid to the local trading agent. The bid price is restricted between the open set limit $(C_{elec_t}, C_{\text{FIT}})$ for a feasible market structure. The rationale behind this limit is the fact that sellers can sell their excess energy to the grid at FIT and buyers can buy the required energy from the grid at electricity tariff. Therefore, this limit encourages the parking lots to trade energy with one another and, thus, comprise a community of energy buyers and sellers

without any (or nearly any) direct influence from the grid so that the price signal from the central power station may not affect the performance of the transactive trading the way it influences the scheduling and trading of energy in existing systems [29].

To be successful in the auction, buyers with large valuation place higher bids closer to utility tariff and sellers with large negative valuation bids close to the feed-in tariff. Eq. (18) shows the bidding price formulation. Σ_p is the choice factor for selecting the bidding range which is a private value and can be changed without notifying the local trading agent. The choice factor is chosen large for buyers with large energy valuation to provide them with wider bidding price range within the price limit (C_{elec_t}, C_{FIT}). The higher value of choice factor results in higher bid prices for buyers, thus increasing the chances of their bid acceptance.

$$E_{val_{t,p}} = E_{Req_{t,p}} - E_{Exc_{t,p}}^{avg} \qquad for\ p \in p_{buy} \tag{17}$$

$$C_{bid_{t,p}} = \frac{C_{elec_t} - C_{FIT}}{2} * \frac{E_{val_{t,p}}/\sigma_p}{\sqrt{1 + \left(E_{val_{t,p}}/\sigma_p\right)^2}} \tag{18}$$

The bid Bid_p of a buyer $p \in p_{buy}$ comprises of bidding price and E_p^{max}, maximum energy demand (charging demand of the parking lot). Note that this energy demand is the maximum energy which the buyer is interested in buying from the transactive trading. Due to flexibility, the bid is not necessarily same as the desired demand rather depends on choice factor too. The energy bid of a buyer can be represented as:

$$Bid_p \equiv \left(C_{bid_p}, E_p^{max}\right) \qquad \forall p \in p_{buy} \tag{19}$$

The bid formulation is same way for sellers.

Market clearing mechanism:

The local trading agent allocates the energy as per the bid offers received from the participants. With distinct participants having distinct bid values based on their energy valuations and choice factor, an auction-based mechanism is ideal for evaluating such trading. The transactions are risk-averse in nature as bids outside the limit (C_{elec}, C_{FIT}) are excluded, hence, there is no loss for any participants. The local trading agent arranges the received bids from buyers in descending orders and gives priority to buyers with high energy valuation and high choice factor and matches them with seller's bid.

The double-sided auctions are based on bids submission from multiple buyers and sellers. Due to generic formulation, the proposed bidding system does not depend on the number of buyers and sellers. For optimum allocation of the energy, an optimization problem is formulated. The market-clearing mechanism is illustrated in figure 5. As the bids of buyers 1 and 2 higher than the market-clearing price, they can purchase their required energy quantity. Also, buyer 3 can only buy a certain amount of the required energy as its bid value is less and the excess energy to be

traded has exhausted. However, buyer 4 will not purchase any amount of energy due to its bid value being lower than the market-clearing price.

Eqs. (20) and (21) represent the system operation cost in the proposed case for buyer and seller parking lots.

$$C_{tot} = \left\{ \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(\left(P_{g2v_{i,t,p}} - \frac{E_{buy_{t,p}}}{\Delta t} \right) * C_{elec_t} + P_{v2g_{i,t,p}} * C_{deg} + \left(P_{PV2EV_{i,t,p}} + P_{PV2G_{t,p}} \right) * C_{PV} \right. \right.$$

$$\left. \left. - \left(P_{v2g_{i,t,p}} + P_{PV2G_{t,p}} \right) * C_{FIT} \right) + \sum_{p=1}^{P} \sum_{t=1}^{T} \left(\frac{E_{buy_{t,p}}}{\Delta t} \right) * C_{bid_{t,p}} \right\} * \Delta t \qquad p \in p_{buy}$$

(20)

$$C_{tot} = \left\{ \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(P_{g2v_{i,t,p}} * C_{elec_t} + P_{v2g_{i,t,p}} * C_{deg} + \left(P_{PV2EV_{i,t,p}} + P_{PV2G_{t,p}} \right) * C_{PV} \right. \right.$$

$$\left. \left. - \left(P_{v2g_{i,t,p}} - \frac{E_{sell_{t,p}}}{\Delta t} + P_{PV2G_{t,p}} \right) * C_{FIT} \right) + \sum_{p=1}^{P} \sum_{t=1}^{T} \left(\frac{E_{sell_{t,p}}}{\Delta t} \right) * C_{bid_{t,p}} \right\} * \Delta t \qquad p \in p_{sell}$$

(21)

The optimization problem is solved by minimizing the operation cost bounded by the energy constraint represented in (22-24).

$$\sum_{p=1}^{p_{buy}} E_{buy_{t,p}} \leq E_{t,p}^{max} \tag{22}$$

$$\sum_{p=1}^{p_{sell}} E_{sell_{t,p}} \leq E_{Exc_{t,p}} \tag{23}$$

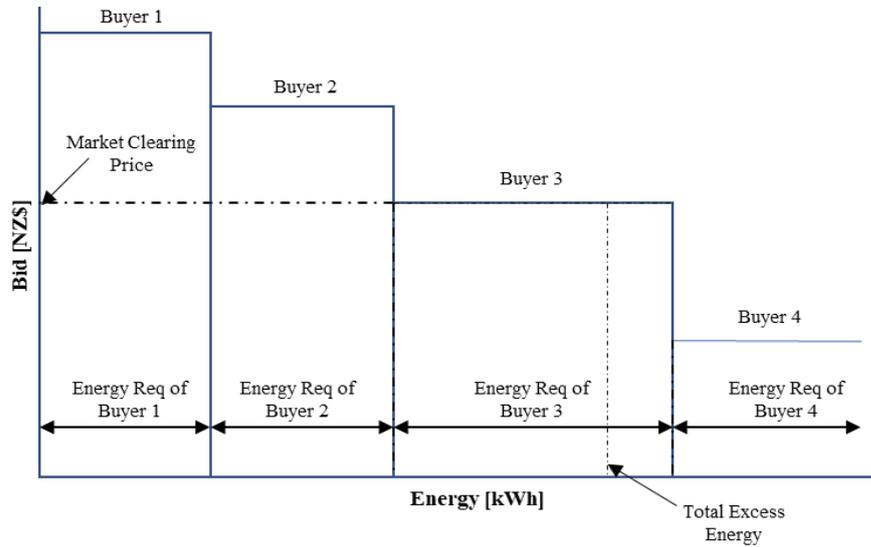$$0 \leq E_{buy_{t,p}} \text{ or } E_{sell_{t,p}} \tag{24}$$

Figure 5: Market clearing mechanism.

The optimization problem formulated involves the multiplication of a binary variable with a continuous variable, thus making it non-linear in nature. To linearize the optimization problem, a new continuous variable 'x' is introduced as shown in (25), which is linearized with the help of constraints shown in (26-28).

$$x = b * c \tag{25}$$

$$x \leq c \tag{26}$$

$$x \geq c - (1 - b) * M \tag{27}$$

$$x \leq b * M \tag{28}$$

where, b represents the binary variable, c represents continuous variable and M represents a set of a very large number. If $b = 0$, the variable x will also be 0 as per (28). However, if $b = 1$, then x will be equal to c as per constraints (26) and (27). Accordingly, x will show values either 0 or c based on these constraints. For more details, [30] can be referred to.

VI. UNCERTAINTY ANALYSIS

The uncertainty present in the forecasting can be divided into two values: expected data value and forecasting error. The uncertainties present can be estimated using the probability distribution function. In this paper, uncertainties present in PV output and electricity prices are considered in the terms of discrete type probability distribution adopted from [31]. Eqs. (29) and (30) presents the discrete probability distribution sets for PV generation (D_{PV}) and electricity prices (D_{G2V}):

$$D_{PV} = (P_{PV}^1, \rho_{PV}^1); (P_{PV}^2, \rho_{PV}^2); \dots; (P_{PV}^n, \rho_{PV}^n) \tag{29}$$

$$D_{elec} = \left(C_{elec}^1, \rho_{elec}^1\right); \left(C_{elec}^2, \rho_{elec}^2\right); \dots; (C_{elec}^n, \rho_{elec}^n) \tag{30}$$

where each set is the pair of expected value and its probability, ρ denotes the probability and n is the total number of scenarios. Also, the sum of all the probabilities is unity for any variable, as shown in (31).

$$\sum_{i=1}^{n} \rho_{PV}^i = \sum_{i=1}^{n} \rho_{elec}^i = 1 \tag{31}$$

Eq. (32) represents the possible scenario sets which can be generated.

$$S = D_{PV} D_{elec} \tag{32}$$

The objective function developed earlier has been modified to include the uncertainties, shown in (33). When solving the optimization problem, the objective function will be multiplied by the joint probability of each scenario created, and the summation of joint probabilities for all scenarios must be equal to one.

$$Min \left\{ \sum_{s=1}^{n} \rho^s \left(\left(\sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} P_{g2v_{i,t,p}} * C_{elec_t} + \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} P_{v2g_{i,t,p}} * C_{deg} + \right. \right. \right.$$

$$\sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(P_{PV2EV_{i,t,p}} + P_{PV2G_{t,p}} \right) * C_{PV} - \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(P_{v2g_{i,t,p}} + P_{PV2G_{t,p}} \right) * C_{FIT} \right) *$$

$$\left. \left. \Delta t \right) \right\} \tag{33}$$

The first term in (33) denotes the expected cost of buying electricity from the utility in the scenario s. The second term is the cost due to battery degradation which is not uncertain so it will

remain the same as the original. The third term is cost due to marginal cost of PV which depends on uncertain PV output, so, it denotes the expected marginal cost of PV in scenario *s* and likewise. The modified optimization model is subjected to all the constraints defined earlier. Note that all the variables associated with the constraints now include the index for the scenario, *s*, as well.

For studying the impact of uncertainty, a set of five different discrete probability distribution for the uncertain variables PV output and electricity price are considered. The objective of considering multiple discrete probability distributions is to showcase the impact of multiple deviations of uncertain paraments (PV output and electricity price) on the net cost savings. The deviations considered are two levels (+5% and +10%) of positive deviation (i.e., higher than forecasted value), two levels (-5% and -10%) of negative deviation (i.e., lower than forecasted value), and zero deviation (i.e., the same as forecasted value). Therefore, 22 distinct scenarios were considered by choosing all possible combinations of these deviations. Table VI shows the details of the discrete probability distribution functions (values and the probability of occurrence), where expected x% means the expected value is x% of the forecasted value.

TABLE IV
DETAILS OF PROBABILITY DISTRIBUTIONS

	PV Generation	Electricity Price
Expected	Probability	
110%	0.05	0.10
105%	0.10	0.15
100%	0.70	0.50
95%	0.10	0.15
90%	0.05	0.10

VII.   RESULTS AND DISCUSSION

To demonstrate the feasibility of the proposed auction system, a comparative analysis has been done. The optimization problem is solved using CPLEX solver on neos-server [32]. The base case employs optimal charging to minimize the system cost. The excess energy is traded back into the grid. For the proposed model, the study case also employs the optimal charging to minimize the system cost. However, the excess energy is not sold back into the grid but traded to other parking lots based on auction mechanism discussed in the last section.

This paper considers six EV parking lots each equipped with a 10 kW$_p$ PV system. The total number of EVs participating in V2G per parking lot is assumed to be 25. The auxiliary power consumption of parking lots is not considered.

The battery degradation cost due to the V2G is 0.065 NZ$ per kWh obtained from [33]. For more realistic analysis, the PV output energy is not considered free. The LCOE for PV is taken as 0.12 NZ$ per kWh taken from [34]. The optimization is done for a 24-hr cycle from 12 am to 11.59 pm. The value chosen for fixed FIT is 0.08 NZ$/kWh and for variable FIT, it is 80% of utility price [35].

Table IV shows the daily cost comparison between the proposed and base model with the variation in FIT. The proposed model achieves cost reduction varying from 4% to 7% for different types of FIT. The variation of system operation cost for the base case and the proposed case are shown in Figure 6 and Figure 7, respectively.

TABLE V
COMPARISON OF CHARGING COST WITH VARIATION IN FIT

	Fixed FIT (NZ$)	Variable FIT (NZ$)
Base model	104.04	107.37
Proposed model	96.53	102.61
Cost reduction	**7.2 %**	**4.76 %**

The PV self-consumption variation (usage of PV power to charge the EVs) is illustrated in Fig. 8. The coincidence of peak electricity pricing with maximum PV power generation happens in the defined time interval [11 am - 4 pm]. However, due to PV marginal cost, i.e., LCOE is higher than utility tariff, the EMS prefers to trade the excess energy to other parking lots to minimize the overall cost.
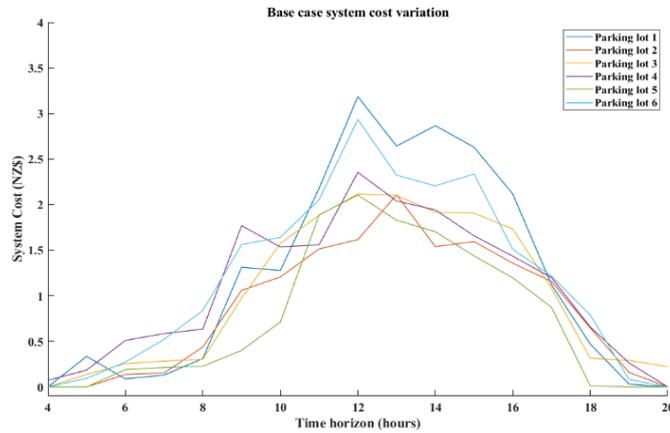
Figure 6: System cost variation for the base case.
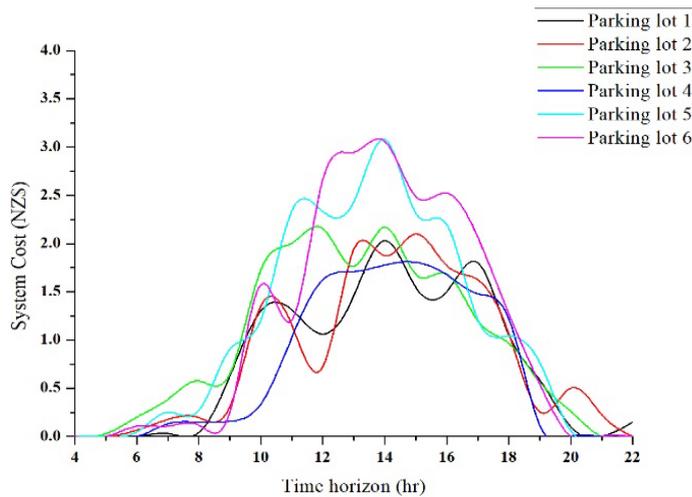
Figure 7: System cost variation for the proposed case.

This results in lower PV utilization for the proposed case as compared to the base case for the fixed FIT. However, with the marginal cost of PV generation decreasing rapidly over the years, the proposed mechanism will increase the PV utilization resulting in lower system operating costs.

Figure 8: PV self-consumption.

Figure 9 shows the bidding price variation for the buyers. Due to the higher energy requirement, the valuation is higher for buyer parking lot 5. Therefore, a higher choice factor is chosen to give more chance of bid being accepted. However, the EMS does not go much higher, as it will increase the charging costs. The buyers' auction characteristics are tabulated in Table V.
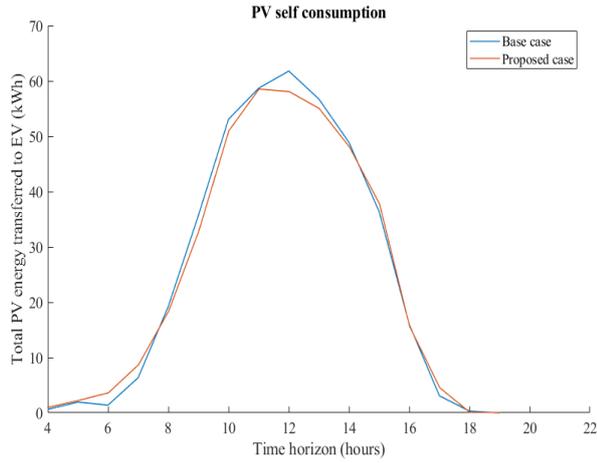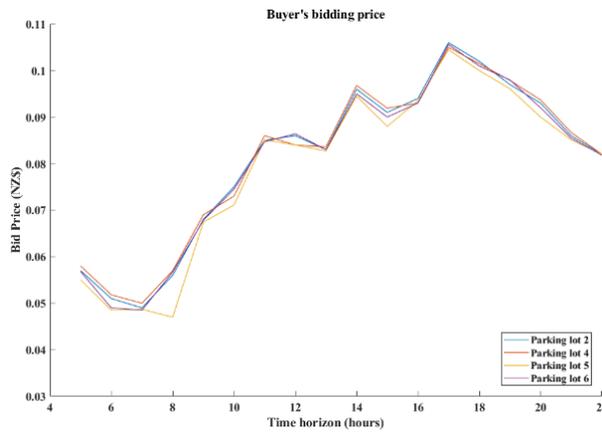

Figure 9: Bidding price of buyers.

TABLE VI
BUYERS' AUCTION CHARACTERISTICS

	Req Energy [kWh]	Energy Valuation [kWh]	Choice factor
Parking lot 2	91.02	57.24	3
Parking lot 4	98.58	64.80	5
Parking lot 5	57.21	23.43	2
Parking lot 6	42.58	8.8	2

To study the uncertainty impact from PV generation and electricity prices on the system, the impact of every combination of scenarios was investigated on the objective function. Upon simulating each scenario, the statistical analysis shows that the cost savings vary from a minimum of 2.41% to a maximum of 12.09% with an average of 6.11% and variance 4.41%.

For evaluation of uncertainty impact of connected EVs on the performance of proposed system, Eq (2) which represents EV arrival and departure times is varied by ±5%. Figure 10 shows the variation of system charging cost with different scenarios.
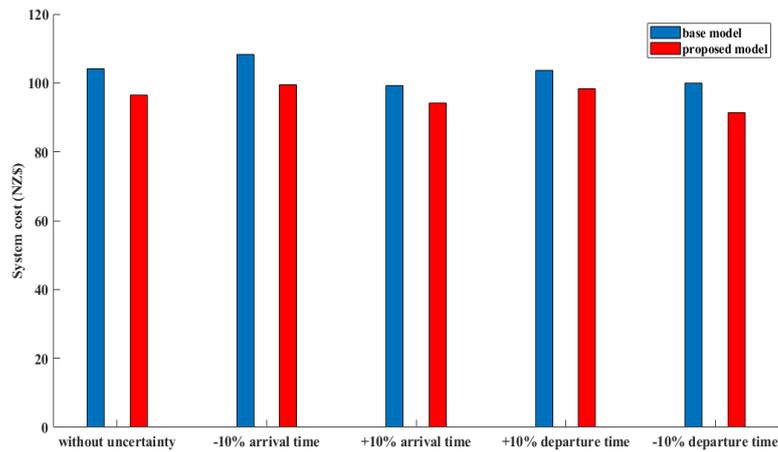
Figure 10: System cost variation with uncertainty in connected EVs.

VIII. CONCLUSION

This work studied the optimal charging problem of the renewable energy integrated EV parking lots. A transactive Energy Management System with satisfactory forecasting accuracy is proposed. To make the model more realistic, the marginal cost of PV generation is considered. However, due to the high marginal cost of PV generation compared to the off-peak utility tariff, the charging costs become higher for large PV consumption. A double-sided auction-based trading method is proposed to mitigate this issue, in which parking lots trade excess energy amongst themselves based on energy requirement of buyers. For a system with 6 parking lots and 25 EVs in each parking lot, the proposed scheme results in cost savings in the range of 2% to 7% for different cases of fixed and variable FIT. These results illustrate the effectiveness of the proposed bidding mechanism. The uncertainty analysis shows that the cost savings vary from a minimum of 2.41% to maximum 12.09% with an average of 6.11%. The parking lots are assumed to be cooperative in nature, however, competitive trading based on a strategic game can be investigated in future.

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Chapter 5: Manuscript 4 - TEMS for range anxious EVs

This manuscript extends the Transactive Energy Management System (TEMS) presented in Chapter 4 by investigating the impact of research anxiety of EV users. The TEMS is optimized with the aim of minimizing overall system costs. Furthermore, the impact of presence of public charging stations on TEMS is also analyzed. The transactive trading mechanism is incorporated with practical parameters like driving distance, forecasting of PV generation, battery degradation, electricity prices, etc., to assess the system close to actual conditions accurately. The number of discharging EVs plays a crucial role in determining cost savings, particularly concerning the availability of public charging stations. Another pivotal factor affecting cost savings is also being researched, which is the distinction between peak and non-peak electricity network pricing periods. The manuscript underscores that during non-peak times, when transactive energy trading occurs, the system cost may occasionally surpass that of the distribution network. In such instances, the primary benefit of transactive energy trading is mitigating EV range anxiety.

Transactive Energy Management of Solar-Based Range Anxious Electric Vehicle Integrated Parking Lots

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Abstract

Electric vehicles (EVs) are regarded as essential solutions for alleviating climate change and energy crises. EVs can store excess Photovoltaic (PV) generation and transfer energy to other EVs, reducing distribution network upgrade costs. However, the limited range of EVs coupled with inadequate charging infrastructure leads to range anxiety among EV users, thereby becoming a barrier to implementing a transactive energy management system. This research quantifies the range anxiety among EV users and proposes a novel trading mechanism for transactive trading between workplace EVs. The case study solved for a commercial region in Auckland shows a 3% to 10% reduction in charging cost compared to a conventional V2G system. Further analysis shows that public charging stations can also result in cost savings from 1% to 5%. Still, their impact is limited compared to the number of discharging EVs participating in transactive trading. The uncertainty analysis of PV generation under different scenarios also shows the cost savings of the proposed strategy. The simulation results verify the feasibility and effectiveness of the proposed strategy while alleviating range anxiety among EV users.

Keywords: Electric Vehicles, Transactive Energy Management, PV, Optimization

Introduction

Electric vehicles (EVs) are becoming increasingly popular due to their many benefits, including reduced environmental impact, lower operating costs, and improved performance over traditional gasoline-powered vehicles. With zero tailpipe emissions and the ability to use renewable energy sources for charging, EVs are a cleaner alternative to gasoline-powered cars, which helps to reduce our reliance on finite fossil fuels, thereby reducing energy import dependency, air pollution and climate change. As the technology advances, EVs are becoming more practical for everyday use, with longer ranges and a growing number of charging stations available.

With fossil fuel-based electricity generation a significant contributor to climate change, renewable energy-based generation like Photovoltaic (PV) is becoming increasingly crucial for a sustainable and cost-effective mode of electricity generation. Due to a mismatch between peak PV generation period and peak load consumption, energy storage is required for reliability, flexibility and higher utilization. As EVs spend most of their time in a parked state, their batteries can be effectively utilized to store excess PV generation for usage at peak load periods in the evenings. This is

known as Vehicle-to-Grid (V2G), and much research has been done on this topic covering all aspects [1]. However, using EVs as dynamic energy storage can lead to range anxiety among drivers. Range anxiety refers to the fear of running out of charge while on a long journey or being unable to find a charging station when one is needed. This concern is the main barrier to widespread EV adoption as mainstream EVs have a limited range compared to gasoline-powered vehicles, and charging infrastructure may be less widely available in some areas [2].

EV users experiencing high-range anxiety with large commutes or busy charging station occupiedness will choose to charge their EVs despite peak load periods with high electricity prices. In comparison, EV users with short commutes or high battery State of Charge (SoC) can provide necessary charging power to high-range anxiety users and profit despite delivering power at a lower cost than the network distribution prices. This will reduce the peak demand of the distribution network.

The potential of EVs transferring energy to one another has been a research focus in recent years. This is also known as transactive energy systems and has been shown to reduce the distribution network upgradation cost, load levelling and reduction in charging costs [3]. Ref [4] presents game theory based on conflicting transactive energy management systems between residential consumers owing EVs and utilities to improve network voltage profile and consumer profits. The work in [5] employs EVs to minimize peak price reduction with minimum information transfer without accounting for the driver's flexibility. Ref [6] proposed a multiagent transactive trading mechanism with the goal of maximizing cost savings for consumers and minimizing the overloading of distribution transformers. However, the transactive model lacks price and user range flexibility. A centralized residential transactive energy management system is proposed in [7] with integrated PV consumers to optimize energy cost and self-reliability. However, the consumers' flexibility and energy storage heath aren't considered. Ref [8] proposes a transactive energy trading mechanism to minimize the electricity purchase cost of EVs. The work considers uncertainty in EVs arrival and departure time but assumes the inflexible participation of EV users. In [9], a game theory-based transactive energy management is presented for residential customers incorporating energy storage, EVs and flexible loads to improve the load profile of the network. A local energy market-based energy management system is proposed in [10] between residential consumers, a distribution network and a centralized energy storage system to maximize revenue generation and optimal resource allocation of all participants. A utility function is considered to approximate consumers' preference to purchase from either a neighbour or a central system. Still, the choice to opt out or make an urgent request (based on imminent energy requirements) is not modelled. A blockchain-based intelligent transactive trading contract between EVs and distribution networks is present in [11] to minimize electricity purchase costs without considering the user's flexibility and input parameters uncertainty.

The existing literature on transactive energy management between EVs generally does not account for the range anxiety of EV users, which is a significant factor for EV participation in transactive energy transfers. Some research works [12], [13] consider range anxiety but do not account for the practical parameters like trading mechanisms, stochasticity of EV demand and electricity price and uncertainty present.

The main contribution of this research can be highlighted as follows:

- This paper proposes a novel transactive trading mechanism for EVs accounting for the range anxiety of EV users.
- The proposed transactive trading mechanism is incorporated with practical parameters like driving distance, forecasting of PV generation with uncertainty analysis, battery degradation, electricity prices, etc., to assess the system close to actual conditions accurately.
- The proposed system is optimized for minimum cost and verified with a comparison with conventional transactive systems for a commercial region in Auckland, New Zealand.

The rest of the paper is organized as follows: The system modelling is introduced in Section II. Section III shows the forecasting of required inputs: PV and charging demand. The trading model is presented in Section IV, with case study simulation, results and discussion in Section V. Finally, the paper's conclusions and future research are provided in Section V.

System Modelling

Multiple commercial parking lots based in Auckland are considered in this paper. The load demand of each parking lot to fulfil its charging demand is through power supplied from the PV system and distribution grid. The model of the system is shown in Figure 1. Abundant charging points are assumed to be available in each parking lot through a modular converter [14]. All system components communicate with each other through microcontrollers attached to them.
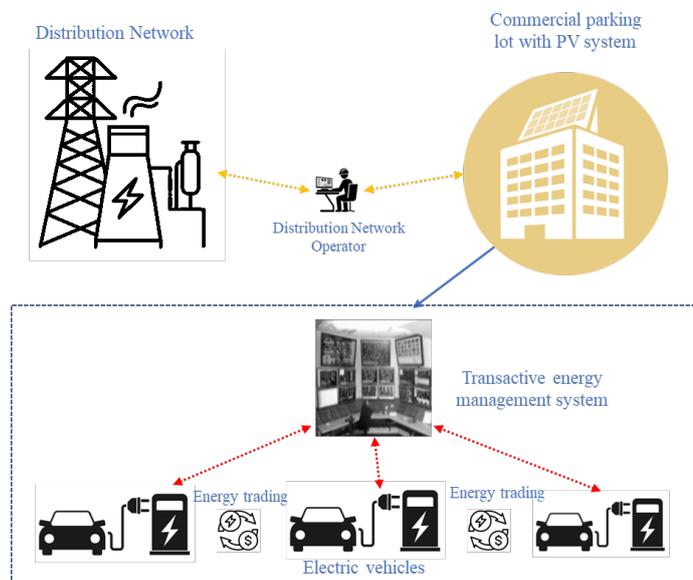

Figure 1: Model of the proposed transactive system

The Energy Management System (EMS) is responsible for ensuring optimal operation conditions for a system involving photovoltaic (PV) output, electricity prices, electric vehicle (EV) demand, and EV charging/discharging. The EMS uses forecasting to anticipate PV output and electricity prices and coordinates the charging/discharging of EVs through charging controllers. The EMS also acts as an aggregator, making decisions about charging and discharging individual EVs based on factors such as the initial state of charge (SoC), target SoC, parking duration, and charging cost. The EMS's role in the system can be broken down into three stages: forecasting, balancing EV demand with supply, and participating in transactive energy trading to minimize costs. The EMS estimates the overall energy demand and PV generation for each hour. It communicates excess energy availability to a local trading agent, who manages an auction process for buying and selling energy.

The local trading agent oversees an auction mechanism through which buyers and sellers submit bids for energy transactions. The EMS in the aggregator (parking lots) estimates the overall energy demand and PV energy generation for each hour and then balances supply and demand. The EMS also evaluates the excess available energy and communicates this value to the local trading agent, who broadcasts the average available extra energy. Buyers who require energy privately assess their energy needs and place bids with the local trading agent. At the same time, sellers also submit bids for selling excess energy based on their private assessments. The local trading agent then uses a double-sided auction method to clear the market and allocate energy based on the collected bids.

Forecasting

Forecasting is an essential step for effective EMS designing for EV charging management, as it helps predict the future relevant inputs and ensure sufficient capacity to meet this demand. Accurate forecasting can help to optimize the use of charging infrastructure, better utilize the PV generation, and improve customer satisfaction by optimizing EV usage. This section presents the forecasting of PV generation and EV demand.

PV Output Forecasting

There are three main approaches to predicting the output of photovoltaic (PV) systems: physical models, statistical models and neural networks-based models. While all the methods can be effective, statistical models are generally considered easily interpretable and more reliable for short-term or intraday forecasting. Among statistical methods, Autoregressive Integrated Moving Average (ARIMA) models have been found to be remarkably accurate at low temporal resolutions. Hence, ARIMA is used to forecast the PV output in this work. The yearly irradiation and temperature data were taken from the National Institute of Water and Atmosphere for Auckland, New Zealand [15].

ARIMA is a statistical model used for forecasting time series data. It is a linear model that assumes that the underlying data follows a specific pattern, such as a trend or seasonality, and that this pattern can be captured using a combination of autoregressive (AR), integrated (I), and moving average (MA) terms. The AR terms in an ARIMA model capture the autocorrelation in the data, which refers to the relationship between the current value of the time series and previous values. The I term represents the integration of the time series, which helps to remove any non-stationarity (trend or seasonality) from the data. The MA terms capture the error or noise in the data, which is assumed to be a random process. The ARIMA model is extended to seasonal ARIMA (SARIMA) to account for periodic patterns in the irradiation data. In addition to ARIMA's three components, SARIMA models include seasonal terms. The seasonal terms have seasonal autoregression (SAR), seasonal integration (SI), and seasonal moving average (SMA). The SARIMA process can be represented using the notation (p,d,q) x (P, D, Q)s. In this case, the chosen SARIMA model has the parameters (p=3, d=0, q=2) x (P=1, D=0, Q=1)s=24, which are listed in Table I.

TABLE I
SARIMA MODEL PARAMETERS

Parameters	Value (PV Forecasting)
AR (2)	0.813
AR (3)	-0.813
MA (1)	-1.051
MA (2)	-0.51
Seasonal AR (1)	0.995
Seasonal MA (1)	0.889

To evaluate the adopted SARIMA model, R2 and root-mean-square error are examined, which amount to 0.938 and 62 W/m2, respectively. Therefore, the selected model is suitable for forecasting.
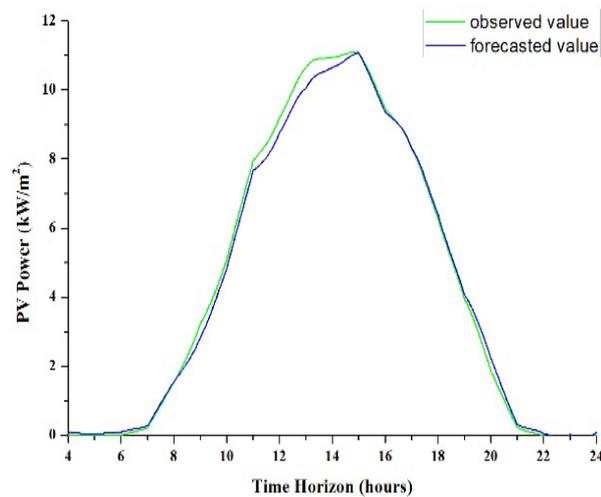

Figure 2: Single-day profile of observed and forecasted PV power

Figure 3 shows a comparison of a daily profile of predicted PV power and observed PV power. Monocrystalline PV panels with an efficiency of 19% are considered here. The generated PV output is computed from the forecasted irradiation [16].

$$P_{PV_t} = \eta A_{PV} G_F \left(1 - \frac{T_C - 25}{200}\right)$$ (1)

where η = efficiency of PV module,

A_{PV} = PV module's surface area (m²)

G_F = forecasted solar irradiation (kW/m²)

T_C = panels' operating temperature (°C).

EV Charging Demand

The parking lots are assumed to cater to mostly workplace EV users. Hence, the parking occupancy is related to working hours from 9.00 a.m. to 5.00 p.m. The distribution of EV arrival and departure times are assumed to be normally distributed based on (2).

$$f(t_i) = \frac{1}{\sigma_t \sqrt{2\pi}} e^{-\left[\frac{(t_i - \mu_t)^2}{2\sigma_t^2}\right]} \qquad t > 0$$ (2)

where $i = \{1, 2, \dots N\}$ represents *ith* EV, σ_t and μ_t are mean and standard deviation respectively. Table II shows the EV distribution characteristics adopted from [17].

TABLE II
EV PROBABILITY DISTRIBUTION PARAMETERS

	Initial SoC	Departure SoC	Arrival	Departure
Mean (h)	1.7	2.07	9 am	5 pm
St. Deviation (h)	0.73	0.52	1	1

The EV fleet composition in Auckland comprises many different types of EVs with varying battery capacities from 9 to 60 kWh [18]. Ref. [19] shows that workplace charging only extends the range of EVs and does not charge them completely. In the literature, the battery energy content or SoC is often represented using uniform [20], normal [21] and log-normal [22] probability functions. In this context, a log-normal distribution function with a maximum and minimum SoC limit of 0.9 and 0.1, respectively, is assumed as per (3).

$$f(SoC_i) = \frac{1}{SoC_i \times \sigma_{SoC} \sqrt{2\pi}} e^{-\left[\frac{(\ln SoC_i - \mu_{SoC})^2}{2\sigma_{SoC}^2}\right]} \qquad SoC > 0$$ (3)

Table III shows the EV characteristic data.

TABLE III
EV CHARACTERISTIC PARAMETERS

Model	Battery capacity [kWh]	Max charging power [kW]	No per parking lot
Mitsubishi Outlander	13.8	3.7	3
Hyundai Ioniq	38.3	7.2	3
Tesla Model 3	55	7.4	3

Toyota Prius	8.8	3.3	6
Nissan Leaf	40	3.6	10

Transactive Energy Management Modelling

This section describes the mathematical modelling of a transactive energy management system.

EV Modelling

The EV charging process is generally nonlinear in nature, but for this work, it is assumed to be linear for generic problem formulation. The mathematical model of EV charging is adopted from [23].

To model the range anxiety, it is necessary to model the regional traffic system to calculate battery consumption to drive to the destination. Traditional EV travel planning models and optimal path algorithms, such as [24], can be utilized to simulate EV travel behaviour. However, these methods tend to require extensive data sampling and involve complex path optimization, which can be time-consuming and inefficient.

Based on [25], a simple algorithm is used to model optimal path-finding driving behaviour. In this algorithm, the traffic system is approximated by a two-dimensional grid, assuming that all the roads are either parallel or perpendicular to each other. The traffic model then can be easily integrated into a cartesian coordinate system. Figure 3 shows the simplified traffic model based on a cartesian coordinates system. Many different paths can be taken to reach location B from location A. Because of the cartesian coordinate system, the distance between locations A and B will be the same irrespective of the chosen path. The EV driving distance from locations A to B can be calculated in (4).

$$D_{AB} = |y_B - y_A| + |x_B - x_A| \tag{4}$$

where y_A, x_A, y_B, x_B represent the coordinates of the locations A & B.

For the simplicity of the traffic model, obstacles and traffic congestion aren't considered.

Figure 3: A simplified traffic model based on the Cartesian system

However, in real transportation systems, roads may not be orthogonal, and EVs may not travel on the shortest path. Therefore, the normal distribution is introduced to solve the uncertainty problem in driving [25] in (5).

$$f(d_i) = \frac{1}{D_{AB}\sqrt{2\pi}} e^{-\left[\frac{(d_i - \mu_{AB})^2}{2D_{AB}^2}\right]} \qquad d > 0 \tag{5}$$

where D_{AB} is the actual driving distance of EV, and μ_{AB} is the standard deviation parameter.

Electricity Prices

The electricity pricing used in this research is taken from [26] as 30c/kWh for the peak period as fixed pricing and 20c/kWh for the non-peak period. The peak periods considered are from 8 am – 10 am and 5 pm – 7 pm in the winter season.

Range anxiety

EV drivers frequently experience range anxiety while driving. Range anxiety is proportional to the EV's remaining driving distance and inversely proportional to battery power. As a result, the range anxiety of an EV that intends to transact energy can be expressed in (6).

$$R_{i,t} = \frac{SoC_{Max} - SoC_{i,t}}{SoC_{Max}} \times \frac{D_i + D_{i,p}}{\max(D_i + D_{i,p} + BC_i * SoC_{i,t}/\alpha_i)} \tag{6}$$

where SoC_{Max} is the maximum SoC of ith EV, $SoC_{i,t}$ is the SoC of ith EV at time t, D_i is the driving distance between EV and its destination, $D_{i,p}$ is the distance between i^{th} EV and p^{th} parking lot and α_i is the power consumption.

The EV users will be influenced by range anxiety based on the charging capacity of the vehicle. Therefore, the charging demand of EV users can be expressed in terms of range anxiety and maximum/minimum charging capacities in (7).

$$E_{Req_{b,t}} = E_{Min,b} + R_{b,t} \times (E_{Max,b} - E_{Min,b}) \qquad\qquad b \in i_{buy} \tag{7}$$

where $E_{Max,b}$ and $E_{Min,b}$ refer to maximum and minimum energy of bth EV respectively.

The higher the range anxiety EV user has; the higher will be its charging demand.

For the discharging EV users, higher range anxiety will lead to lower available power to trade. Like above, the discharging demand of EV users can also be expressed as in (8).

$$E_{Exc_{s,t}} = E_{Min,s} + (1 - R_{s,t}) \times (E_{Max,s} - E_{Min,s}) \qquad\qquad s \in i_{sell} \tag{8}$$

The total EV participating in transactive energy trading can be constrained by (9)

$$i_{buy} + i_{sell} = N \tag{9}$$

For each parking lot, the average available energy for trading will depend on the power available from discharging EVs and charging demand for charging EVs and PV energy as shown in (10). Eq (11) calculates the average available energy

$$E_{Exc_{p,t}} = \sum_{i=1}^{k}(E_{Exc_{s,t}} - E_{Req_{b,t}}) + P_{PV_{p,t}} * \Delta t \qquad s + b = N \tag{10}$$

$$E_{Exc_{p,t}}^{avg} = \frac{E_{Exc_{p,t}}}{b} \tag{11}$$

Objective Function Formulation

The transactive trading mechanism is adopted from [27], where the energy valuation of each parking lot is calculated based on the required energy to buy, as shown in (12).

$$E_{val_{p,t}} = E_{Req_{p,t}} - E_{Exc_{p,t}}^{avg} \qquad for\ p \in p_{buy} \tag{12}$$

Based on this valuation, each buyer submits its bid to the local trading agent. The bid price is restricted between the open set limit (C_{elec_t}, C_{FIT}) for a feasible market structure. The rationale behind this limit is that sellers can sell their excess energy to the grid at FIT, and buyers can buy the required energy from the grid at an electricity tariff. Therefore, this limit encourages the parking lots to trade energy with one another and, thus, comprise a community of energy buyers and sellers without any (or nearly any) direct influence from the grid so that the price signal from the central power station may not affect the performance of the transactive trading the way it influences the scheduling and trading of energy in existing systems [28].

To be successful in the auction, buyers with large valuations place higher bids closer to the utility tariff and sellers with large negative valuation bids relative to the feed-in tariff. Eq (13) shows the bid formulation, which depends on the energy valuation of each parking lot and is constrained between the limits (C_{elec_t}, C_{FIT})

$$C_{bid_{p,t}} = \frac{C_{elec_t} - C_{FIT}}{2} * \frac{E_{val_{p,t}}}{\sqrt{1 + \left(E_{val_{p,t}}\right)^2}} \tag{13}$$

The bid Bid_p of a buyer $p \in p_{buy}$ comprises of bidding price and E_p^{max}, maximum energy demand (charging demand of the parking lot). Note that this energy demand is the maximum energy the buyer wants from the transactive trading. The energy bid of a buyer can be represented as (14). The bid formulation is the same way for sellers.

$$Bid_p \equiv \left(C_{bid_p}, E_p^{max}\right) \qquad \forall\ p \in p_{buy} \tag{14}$$

The local trading agent allocates the energy as per the bid offers received from the participants. An auction-based mechanism is ideal for evaluating such trading with distinct participants having distinct bid values based on their energy valuations. The transactions are risk-averse, excluding bids outside the limit (C_{elec}, C_{FIT}) to ensure no participant loss. The local trading agent arranges the received bids from buyers in descending order, prioritises buyers with high energy valuation, and matches them with the seller's bid.

The double-sided auctions are based on bid submissions from multiple buyers and sellers. Due to generic formulation, the proposed bidding system is independent of the number of buyers and sellers. For optimum allocation of the energy, an optimization problem is formulated.

$$C_{tot,b} = \left\{ \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(\left(P_{g2v_{i,p,t}} - \frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{elec_t} + P_{v2g_{i,p,t}} * C_{deg} + \left(P_{PV2EV_{i,p,t}} + P_{PV2G_{p,t}} \right) * C_{PV} - \right.$$

$$\left. \left(P_{v2g_{i,p,t}} + P_{PV2G_{p,t}} \right) * C_{FIT} \right) + \sum_{p=1}^{P} \sum_{t=1}^{T} \left(\frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{bid_{p,t}} \right\} * \Delta t \qquad p \, \epsilon \, p_{buy} \qquad (15)$$

Eq. (15) represent the system operation cost in the proposed case for buyer parking lots. A similar operation cost function can be formulated for sellers as well. The total cost function to optimize is shown in (16).

$$C_{tot} = \min \{C_{tot,b}, C_{tot,s}\} \qquad (16)$$

The optimization problem is solved by minimizing the operation cost bounded by the energy constraint represented in (17-19).

$$\sum_{p=1}^{p_{buy}} E_{buy_{t,p}} \leq E_{t,p}^{max} \qquad (17)$$

$$\sum_{p=1}^{p_{sell}} E_{sell_{t,p}} \leq E_{Exc_{t,p}} \qquad (18)$$

$$0 \leq E_{buy_{t,p}} \, or \, E_{sell_{t,p}} \qquad (19)$$

The optimization problem formulated involves the multiplication of a binary variable with a continuous variable, thus making it non-linear in nature. To linearize the optimization problem, a new continuous variable 'x' is introduced, as shown below, which is linearized with the help of constraints demonstrated in (20-23).

$$x = b * c \qquad (20)$$

$$x \leq c \qquad (21)$$

$$x \geq c - (1 - b) * M \qquad (22)$$

$$x \leq b * M \tag{23}$$

where b represents the binary variable, c represents the continuous variable, and M represents a set of a very large numbers. If $b = 0$, the variable x will also be 0 as per (20). However, if $b = 1$, then x will be equal to c as per constraints (21) and (22). Accordingly, x will show either 0 or c values based on these constraints. For more details, [29] can be referred to.

Uncertainty Analysis

The forecasting uncertainty can be categorized into two components: the anticipated data value and the forecasting error. These uncertainties can be quantified using the probability distribution function. This paper quantifies the uncertainties in PV generation by employing discrete-type probability distributions adopted from [23].

Eq. (24) presents the discrete probability distribution sets for PV generation (D_{PV}):

$$D_{PV} = (P_{PV}^1, \rho_{PV}^1); (P_{PV}^2, \rho_{PV}^2); \dots; (P_{PV}^n, \rho_{PV}^n) \tag{24}$$

where each set is the pair of expected value and its probability, ρ denotes the probability and n is the total number of scenarios. Also, the sum of all the probabilities is unity for any variable, as shown in (25).

$$\sum_{i=1}^{n} \rho_{PV}^i = 1 \tag{25}$$

The previously developed cost function in (15) has been updated to incorporate uncertainties, as shown in (26) for buyers. In addressing the optimization challenge, this function will be adjusted by multiplying it with the joint probability associated with each devised scenario. Furthermore, the cumulative joint probabilities across all scenarios will be required to sum up to one.

$$C_{tot,b} = \left\{ \sum_{s=1}^{n} \rho^s \left\{ \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(\left(P_{g2v_{i,p,t}} - \frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{\text{elec}_t} + P_{v2g_{i,p,t}} * C_{\text{deg}} + \right. \right. \right.$$

$$\left. \left(P_{PV2EV_{i,p,t}} + P_{PV2G_{p,t}} \right) * C_{PV} - \left(P_{v2g_{i,p,t}} + P_{PV2G_{p,t}} \right) * C_{\text{FIT}} \right) + \sum_{p=1}^{P} \sum_{t=1}^{T} \left(\frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{bid_{p,t}} \right\} *$$

$$\Delta t \right\} \qquad p \in p_{buy} \tag{26}$$

The initial term in (26) represents the anticipated cost of purchasing electricity from the utility for scenario s. The subsequent term accounts for the cost related to battery degradation, which, being certain, remains unchanged from the original estimate. The third term reflects the cost associated with the marginal cost of PV energy, which varies due to the uncertain output of PV, thus indicating the expected marginal cost of PV in scenario s and likewise. The modified optimization model adheres to all previously established constraints, with each variable now also incorporating

the scenario index, *s*, as well. The cost function for sellers can also be modified in a similar manner before optimizing for total cost as per (16).

To examine the effects of uncertainty, five distinct discrete probability distributions are analyzed for PV generation. The aim of utilizing various discrete distributions is to demonstrate how different degrees of uncertainty in PV generation influences the overall net cost savings. Specifically, the variations include two positive deviations (+5% and +10%, indicating higher than predicted values), two negative deviations (-5% and -10%, indicating lower than predicted values), and a scenario with no deviation (aligning with the predicted values). Thereby, five distinct scenarios were considered with the details of the discrete probability distribution functions (values and the probability of occurrence) shown in Table IV. The expected x% means the expected value is x% of the forecasted value.

TABLE IV
DETAILS OF PROBABILITY DISTRIBUTIONS

Expected	PV Generation Probability
110%	0.05
105%	0.10
100%	0.70
95%	0.10
90%	0.05

Energy Management Algorithm

The following steps highlight the energy management algorithm:

1. EVs with charging and discharging need to use the energy management system platform to search for an appropriate EV parking lot to join. Each EV provides information about its transactions, such as the starting point, destination, and current state of charge.

2. The energy management system platform presents multiple EV parking lot options based on location, available power supply, and charging or discharging prices. Using the information provided by EVs, the platform determines the best parking lot for an EV to join, considering factors such as income, time, and route. This information is then shared with the EV for its reference.

3. Based on the information on the energy management system platform, the parking lot accepts or rejects EVs to minimize the total system cost. Every parking facility evaluates the advantages of various trading options, such as trading with the wholesale market and other EV parking lots. The optimal choice is determined by comparing these benefits, and the parking lot either accepts or rejects EVs accordingly.

4. The transactive energy trading platform accepts bids from each parking lot and clears the market using a double-sided auction mechanism. Based on the amount of excess/required energy after each trading, a parking lot either accepts EVs from other lots or reduces the number of existing ones.
1. The energy management system platform matches EVs based on the parking lot's selection and transaction requests. The EVs (if not already present in a parking lot) then go to the matched parking lot to carry out power transfer. The distance between the EV location and the parking lot determines the time electric vehicles take to reach parking lots.

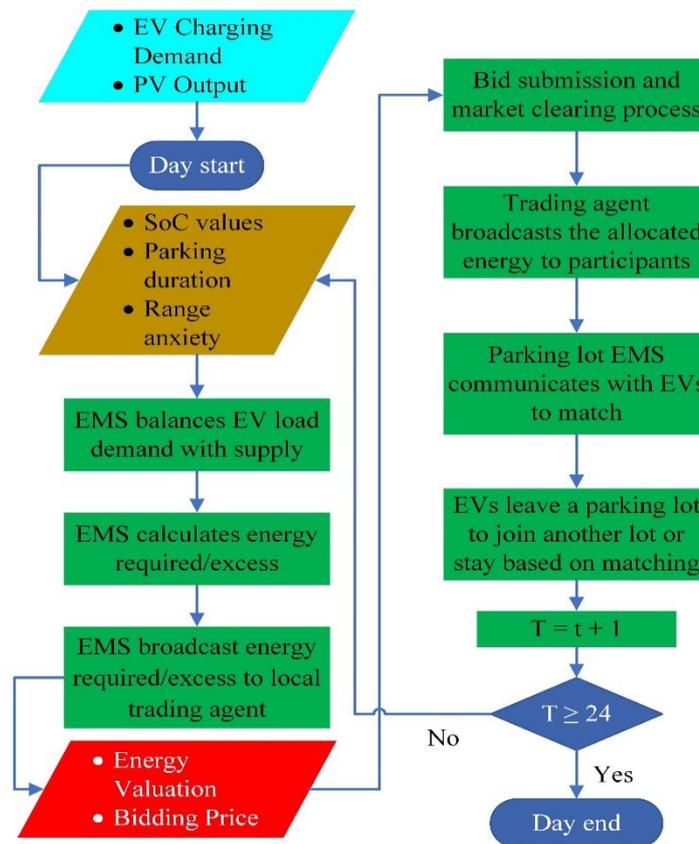The flowchart of the energy management system's strategy is shown in Figure 4.

Figure 4: A flowchart of the EV management system process

Results and Discussion

A comparative analysis has been done to demonstrate the feasibility of the proposed auction system. The optimization problem is solved using a CPLEX solver on neos-server [30]. The base case employs optimal charging to minimize the system cost. The excess energy is sold back into the grid via parking lots as aggregator, not traded with other EV parking lots. For the proposed model, the case study also employs optimal charging to minimize the system cost. However, the excess energy is not sold back into the grid but traded to other EV parking lots based on a bidding mechanism. An additional case is considered here where EVs can also utilize fast public Charging

Stations (CS) to alleviate their range anxiety at commercial prices taken as 10% more than the electricity price.

This paper considers six EV parking lots, each equipped with a 10 kWp PV system. The total number of EVs participating in V2G per parking lot is assumed to be 25. The auxiliary power consumption of parking lots is not considered. Five public charging spots are considered in this paper. Figure 5 shows the spatial locations of EV parking lots (in blue) and public charging spots (in green).
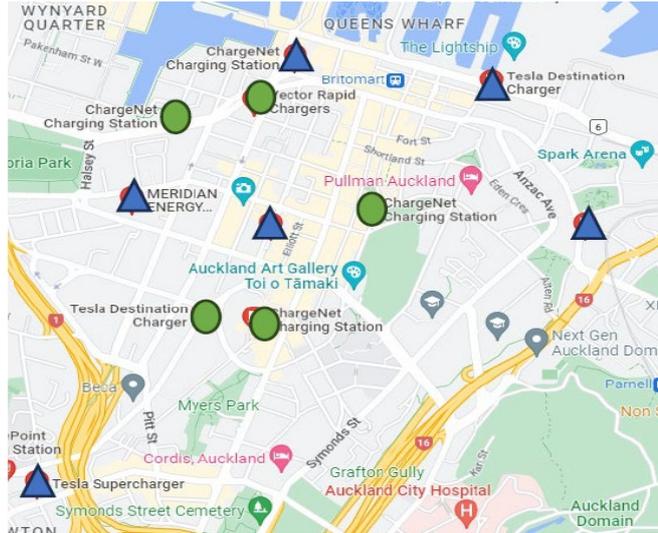

Figure 5: Map of parking lots and public charging stations

The battery degradation cost due to the V2G is 0.065 NZ\$ per kWh obtained from [31]. The PV output energy is not considered free for a more realistic analysis. The LCOE for PV is taken as 0.12 NZ\$ per kWh taken from [32]. The optimization is done for a 24-hour cycle from 12 a.m. to 11.59 p.m. The value chosen for FIT is 0.08 NZ\$/kWh [33].

The daily system cost comparison for the three cases is shown in Table IV. The daily system costs shown are mean (and deviation) when EVs are randomly designated as charging or discharging and simulated 50 times. The higher charging cost at public charging stations results in fewer cost reductions than relying on a transactive trading mechanism.

TABLE IV
COMPARISON OF SYSTEM COST

	Base Model	Proposed Model (without charging stations)	Proposed Model with charging stations
System Cost (NZ\$)	163.72 (152.12 – 191.55)	153.57 (148.3 ~ 174.3)	160.1 (150.3 ~ 179.5)
Cost reduction wrt base	-	6.2 % (2.5 % ~ 9.8 %)	2.2 % (1.3 % ~ 6.4 %)

Variation of the number of charging EVs versus discharging EVs can impact the system cost as fewer discharging EVs lead to more usage of public charging stations or less energy available for transactive trading. Figure 6 shows the impact of discharging EVs on the system cost. More discharging EVs will only sometimes lead to larger transactive energy trading due to demand and supply imbalance, leading to smaller bid amounts.
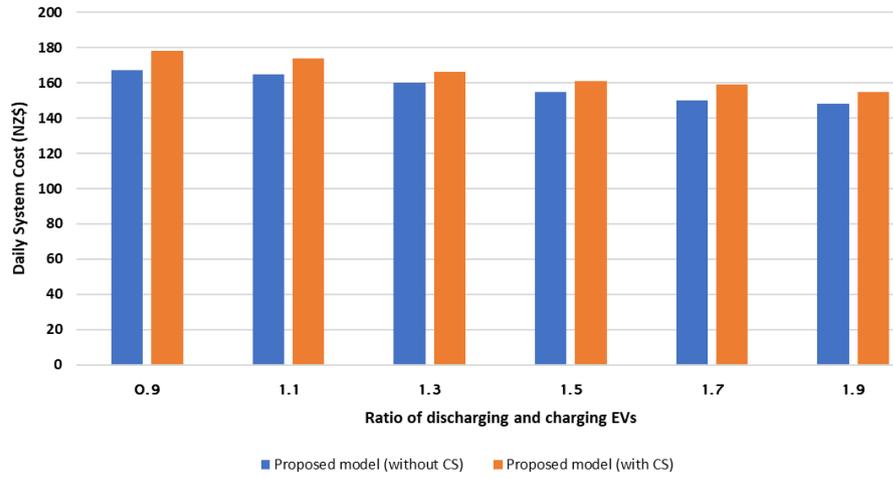

Figure 6: Variation of system cost with respect to the number of discharging EVs

The number of available fast public chargers also impacts the system cost. A higher number of available chargers will increase the system cost as parking lots with higher energy valuation (due to the high range anxiety of EVs) may not succeed in bidding, depending on the excess energy available for transactive trading. Such scenarios will lead to public charging facility usage by range anxious EVs, albeit at a higher cost. Figure 7 shows the variation in system cost when different numbers of charging stations are available while keeping the ratio of charging and discharging EVs at 1.5. Each CS is assumed to accommodate only 2 EVs at a time and level 3 charging capability.
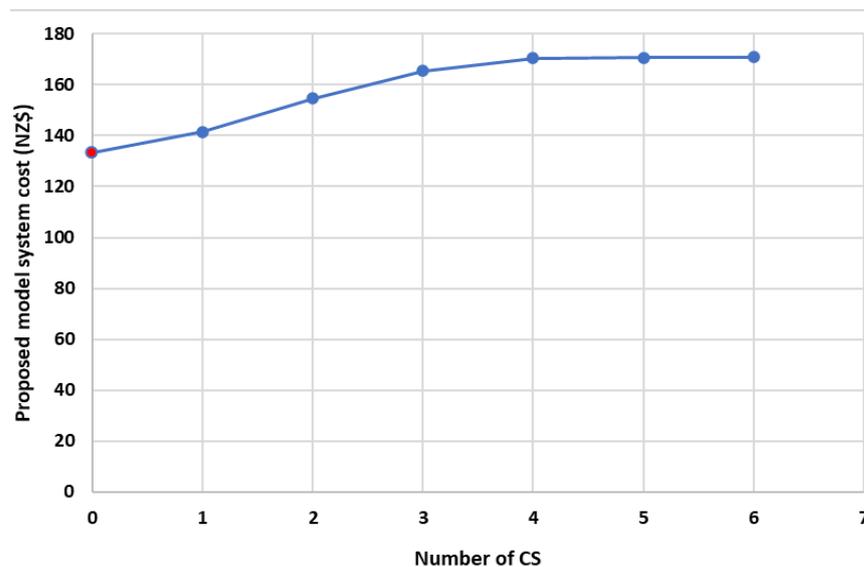

Figure 7: Variation of system cost with number of CS

The system cost saturates with the increased number of charging stations due to non-usage. Additionally, EVs that don't get charging energy from the available excess energy pool (in transactive energy trading) can only choose a public charging station when there is one. The red dot in Figure 7 depicts the system cost, which is relatively cheap because only some of the demand for EVs can be satisfied.

As the bidding price is restricted to be less than the electricity network price for the feasibility of the transactive energy market, it is possible that all EVs couldn't successfully participate in transactive energy trading during the evening peak period. This depends mainly on the number of available discharging EVs. Figure 8 shows the variation in system cost during the day.
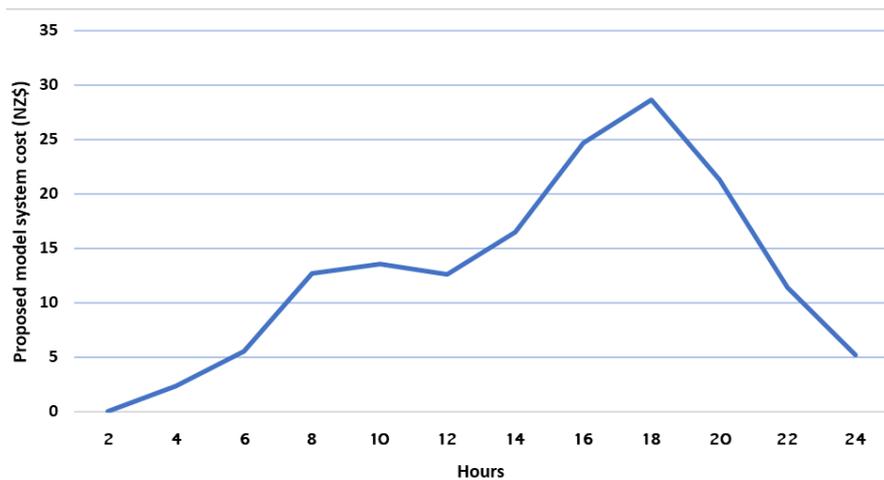
Figure 8: Variation of system cost with time

The uncertainty analysis using discrete probability distribution is performed on five generated scenarios to evaluate the impact of uncertainty in PV generation on the system cost variation. Figure 9 shows the variation of system cost for the base and proposed model in each of these scenarios, where Ppv refers to PV generation.
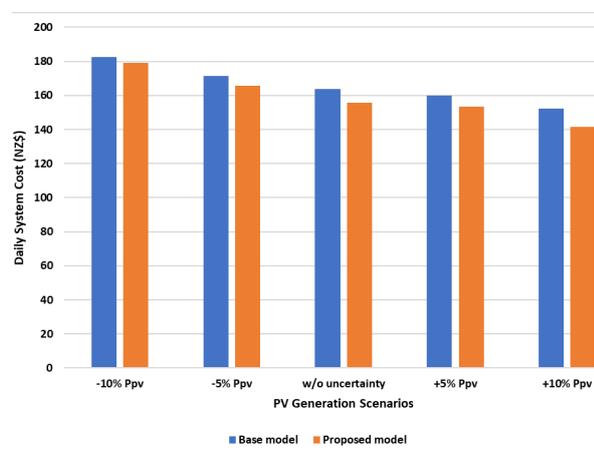

Figure 9: System cost variation with uncertainty in PV generation

Conclusions

Range anxiety is one of the significant barriers for implementation of transactive energy management systems for the EVs. This paper studies the optimal charging problem of the PV integrated range anxious EV parking lots. A transactive energy trading mechanism is proposed to minimize the system cost. The results achieved from this paper can be summarised as follows:

1. The presented trading strategy results in 2% to 8% savings compared to the system cost in EVs relying only on distribution networks and PV energy.

2. Additionally, the presence of public charging stations can also result in cost savings in the range of 1% to 5%.

3. The number of discharging EVs significantly impacts cost savings versus the number of public charging stations.

4. The peak or non-peak period of electricity network pricing also significantly affects the EVs taking part in transactive energy trading compared to charging and discharging into the distribution network. When transactive energy trading occurs at non-peak times, the system cost is generally greater than the distribution network. That instance, transactive energy trading mainly alleviates the EV's range anxiety.

5. The uncertainty analysis of PV generation results in cost savings scenarios ranging from 1% to 9%.

The parking lots are assumed to be cooperative in nature in this paper. However, competitive trading based on a strategic game can be investigated in future.

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Chapter 6: Conclusions and Future Work

1. Introduction

The energy management of EV charging within a transaction trading environment represents a critical and evolving aspect of the transition to sustainable transportation and energy systems. This thesis explores the multifaceted challenges and opportunities associated with optimizing EV charging operations, balancing supply and demand, maximizing renewable energy usage and leveraging transactional frameworks to create a more efficient and cost-effective electric grid.

Through an analysis of various charging management strategies, it is evident that the integration of renewable energy sources and smart grid technologies plays a pivotal role in enhancing the flexibility and sustainability of EV charging. Furthermore, the emergence of local energy trading platforms offers the potential to create a decentralized and democratized energy ecosystem where EVs not only consume electricity but also contribute excess energy back to the grid.

As electric vehicles continue to gain prominence in the transportation sector, their effective integration into the broader energy landscape will require collaboration among stakeholders, including utilities, regulatory bodies, technology providers, and consumers. Additionally, the development of robust charging infrastructure and the implementation of real-time data analytics and optimized trading strategies will be essential for ensuring the reliability and scalability of transactional EV charging systems.

A significant increase in the adoption of EVs necessitates the development of a comprehensive models for optimizing Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) management within the context of transactive energy trading markets. However, EV aggregators face several challenges when it comes to EV participation in local energy trading. These challenges encompass the unpredictable behavior of individual customers and the inherent volatility of electricity market prices. Further uncertainties arise from the integration of a high proportion of variable renewable energy sources (RESs), which could potentially introduce financial risks to the operations of EV aggregators.

Furthermore, certain critical factors must be addressed to make EVs commercially viable and widely accepted for transactive energy market participation. Foremost among these is the issue of range anxiety, which also stands as a significant barrier to the widespread adoption of EVs. Additionally, reducing the cost (or increasing profit) is an important goal for ensuring high EV participation in transactive energy markets. The frameworks proposed and developed within the scope of this thesis effectively mitigate the impact of these challenges, thus facilitating the increased adoption of EVs within the local markets.

2. Conclusions and contributions

Chapter 2 presents a comprehensive literature review on the integration of PVs and EVs in the distribution networks. A general framework of designing the grid connected EV-PV system is described along with a focus on smart charging algorithms. The chapter evaluates different modelling approaches of grid connected EV-PV system. Different methods for modelling the uncertainties present with the various input parameters (EV charging demand, PV generation, and Electrical load distribution) for the EV-PV grid integrated system are also reviewed in the chapter. Furthermore, it discusses the directions of possible research gaps in the area of grid connected EV-PV system to be investigated. The review suggests that there is a need for more research on peer-to-peer or transactive type charging systems as this encourages all types (big, small, etc) EV aggregators to trade energy with one another instead of only sizeable aggregator participating in central energy trading. Another advantage is that transactive trading can operate independently of direct influence from the grid so that the price signal from the central power station may not affect the performance of the transactive trading the way it influences the scheduling and trading of energy in existing systems. Price varying scheduling is very attractive to aggregators because of easy implementation and effectiveness for managing charging load in peak/valley times. Therefore, more research is required for charging models based on price response and price elasticity. Further, the focus of future research should be on finding more realistic forecasting and uncertainty analysis techniques that optimally balance simplicity and performance. Almost all the current research focuses on improving PV forecasting accuracy rather than addressing uncertainties associated with PV generation.

Chapter 3 presents a novel framework for trading between agents in a Local Energy Market (LEM) and the wholesale market through an aggregator. The chapter models the conflicting objectives between the diverse participants (producers and consumers) to achieve maximum overall profits. The uncertainty in PV and wholesale electricity price is reduced through forecasting techniques. The grey wolf optimization algorithm is used for maximizing agents' profits without privacy concerns. The LEM is shown to improve agents profits even with different aggregator's tariff values. In one particular case of producer agent selling at loss, participation in the LEM cannot outweigh the fee variations experimented with the aggregator. Nonetheless, a realistic scenario with the presence of more producers' agents selling energy will outweigh the aggregator cost variations.

Chapter 4 proposes a novel double-sided auction based transactive energy trading model for the PV based workplace EV charging station. A bidding price flexible transactive trading mechanism is developed which provides EV aggregators with wider bidding price range to increase the chances of procuring the required energy need. To make the model more realistic, the marginal cost of PV generation is considered. However, due to the high marginal cost of PV generation compared to the off-peak utility tariff, the charging costs become higher for large PV

consumption. The uncertainty associated with forecasting of PV power and electricity prices is modelled using discrete type probability distribution, which shows the feasibility of the model resulting in cost savings even with $\pm10\%$ errors in forecasting. In summary, the proposed framework considers the flexibility of choice and aims to minimize the system cost while maintaining feasible transactive market structure.

Chapter 5 further extends the framework proposed in Chapter 4 by incorporating range anxiety of EV users in the modelling. The impact of public charging stations is also evaluated with a variation of peak vs non-peak electricity pricing. The number of EVs participating in transactive energy markets as discharging EVs significantly impacts cost savings versus the number of public charging stations. A higher number of discharging EVs alleviates system cost, while a greater number of charging stations only reduce the system cost till a saturation point. A very high number of discharging EVs will only sometimes lead to larger transactive energy trading due to demand and supply imbalance, leading to smaller bid amounts. The peak or non-peak period of electricity network pricing also significantly affects the EVs taking part in transactive energy trading compared to charging and discharging into the distribution network. When transactive energy trading occurs at non-peak times, the system cost may be higher than the distribution network. At this time, transactive energy trading mainly alleviates the EV's range anxiety. The generic problem formulation with the case study using real data from Auckland, New Zealand provides a potential solution for mitigating range anxiety among EVs participating in transactive energy markets.

3. Future Work

Notwithstanding the valuable contributions and findings from this study, there are several possibilities for future research and potential study areas to provide more insights on the subjects addressed in this thesis. Some of the critical research areas needing further investigation are as follows:

1. Non cooperative trading participants

    This research presents the frameworks for transactive energy markets under cooperative behaviours from individual EVs. However, EVs users have their own preferences and constraints which don't follow the expected market behaviour of profit maximization (or cost minimization) in real life. Further research into investigating different types of non-cooperative and competitive behaviours employing game theoretic models will enhance the frameworks presented in this thesis.

2. Probabilistic forecasting of input parameters

    The various input parameters like electricity prices, PV output, load demand etc. used in designing an energy management system for EVs participating in energy trading are deterministically forecasted in this thesis. While the uncertainties in forecasting are

considered, the probabilistic type forecasts make the transactive energy frameworks more risk-averse, flexible and realistic. They allow for more accurate estimation of risk metrics, thereby equipping participants with improved decision making.

3. Transition to Distribution System Operator

   The thesis focuses on reducing the system cost or the charging cost for the participants. From the perspective of a Distribution Network Operator (DNO), the reduced costs of network expansion, local operational constraints and congestion planning would be interesting avenues to be researched. The transition of DNO to Distribution System Operator (DSO) represents a significant shift in the way electricity distribution grids are managed and operated. The coordination of DSO with wholesale energy markets to ensure grid stability and reliability. Information sharing and communication between these entities can be researched further.

4. System stability and reliability

   The thesis focuses on managing the power flow in the distribution network. The future studies can focus on enhancing grid stability as more EVs and PV are integrated into the distribution network by mitigating fluctuations that can lead to instability. Research can delve into advanced grid management techniques, such as dynamic load balancing and frequency regulation, which utilize the storage capabilities of EVs and the variable output of PV systems. By deploying advanced control systems that can predict and mitigate potential disturbances in real time, these technologies will not only ensure a consistent energy flow but also enhance the resilience of the grid against external disturbances. Such efforts are crucial for building a robust grid that can withstand the complexities introduced by decentralized and intermittent energy sources, thereby ensuring a stable and reliable energy framework for the future.