

# 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 3–10% 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.

## 1. 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 upgrade cost, load levelling and reduction in charging costs [3]. Accurate estimation of EV battery parameters is essential for designing a transactive energy management system, as presented in [4]. Ref [5] presents game theory based on conflicting transactive energy management systems between residential consumers owing EVs and utilities to improve

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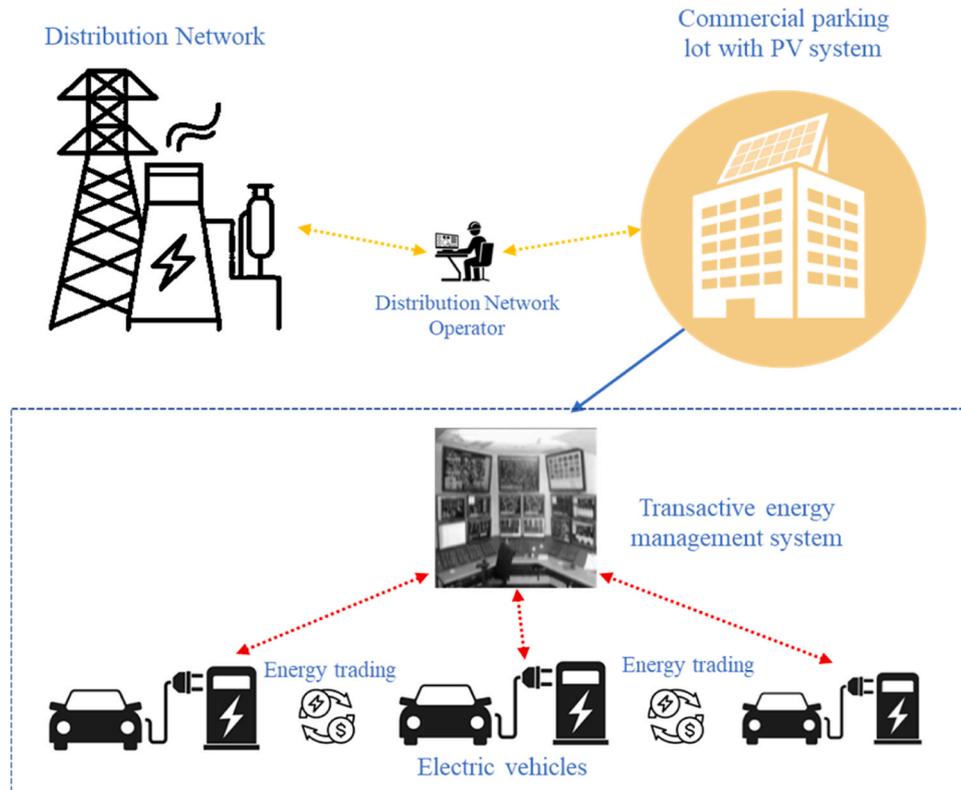


Fig. 1. Model of the proposed transactive system.

network voltage profile and consumer profits. The work in [6] presents the optimal distribution system planning using electric vehicle charging stations using scenario-based optimization. Ref [7] proposed a multi-agent transactive trading mechanism to maximize cost savings for consumers and minimize 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 [8] with integrated PV consumers to optimize energy cost and self-reliability. However, the consumers' flexibility and energy storage health aren't considered. Ref [9] proposes a transactive energy trading mechanism to minimize the electricity purchase cost of EVs. The work considers uncertainty in EVs arrival and departure times but assumes the inflexible participation of EV users. 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 blockchain-based intelligent transactive trading contract between EVs and distribution networks is presented in [11] to minimize electricity purchase costs without considering the user's flexibility and input parameters uncertainty. Ref [12] proposes a transactive-based EV charging scheduling optimization considering user preferences and uncertainties using the Monte Carlo method without accounting for users' range anxiety. A bilateral auction-based transactive trading approach between EVs and aggregators based on decentralized blockchain distribution is proposed in [13]. The scheduling strategy outlined in [14] adopts a hierarchical framework, where each EVSC independently plans its operations to optimize its earnings. This paper employs a single-sided auction mechanism that lacks complete information to execute the market clearing process. A game theory-based transactive trading approach between microgrids is proposed in [15], accounting for forecasting errors in input parameters. A day-ahead optimization of PV-integrated EV charging stations under a transactive energy environment is presented in [16] while considering the uncertainty only in PV generation.

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, like [17] and [18], consider range anxiety but do not account for the practical parameters like trading mechanisms, stochasticity of EV demand, 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 by comparing it with conventional grid-integrated 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, while the case study simulation, results and discussion are elaborated in Section V. Finally, the paper's conclusions and future research are provided in Section V.

## 2. System modelling

Multiple commercial parking lots based in Auckland are considered in this paper. The charging demand of each parking lot is fulfilled through power supplied by the PV system and distribution grid. The system model is shown in Fig. 1. Abundant charging points are assumed to be available in each parking lot through a modular converter [19]. All system components communicate with each other through micro-controllers attached to them.

The Energy Management System (EMS) plays a crucial role in optimizing the performance of a system that involves photovoltaic (PV) output, electricity prices, electric vehicle (EV) demand, and EV charging/discharging. Through the use of forecasting, the EMS anticipates PV output and electricity prices while coordinating the charging/discharging of EVs through charging controllers. Additionally, the EMS serves as an aggregator, making decisions regarding the charging and discharging of individual EVs based on factors such as initial state of charge (SoC), target SoC, parking duration, and charging cost. The EMS's function within the system can be divided into three main stages: forecasting, aligning EV demand with supply, and engaging in transactive energy trading to minimize costs. Specifically, the EMS estimates each hour's overall energy demand and PV generation. It communicates surplus energy availability to a local trading agent, overseeing an auction process for buying and selling.

The local trading agent supervises an auction system wherein buyers and sellers present bids for energy transactions. Within the aggregator (parking lots), the EMS calculates the total energy demand and PV energy production for each hour, striving to balance supply and demand. Additionally, the EMS assesses surplus available energy and relays this information to the local trading agent, who disseminates the average surplus energy to potential buyers. Prospective buyers individually evaluate their energy requirements and submit bids to the local trading agent, while sellers, following their assessments, also submit bids to sell excess energy. The local trading agent then employs a double-sided auction method to clear the market and distribute energy based on the accumulated bids.

### 3. 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 optimize the use of charging infrastructure, better utilize PV generation, and improve customer satisfaction by optimizing EV usage. This section presents the forecasting of PV generation and EV demand.

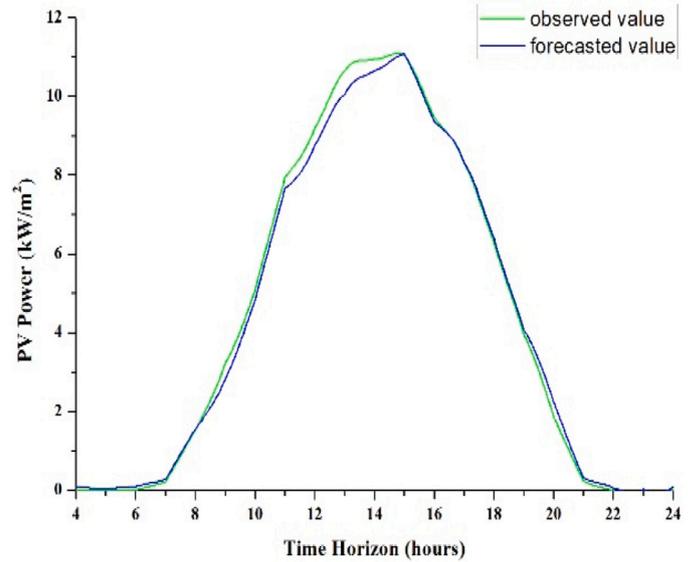
#### 3.1. PV output forecasting

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 (NIWA) for Auckland, New Zealand [20].

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  $(p,d,q) \times (P,D,Q)s$ . In this case, the chosen SARIMA model has the parameters  $(p=3, d=0, q=2) \times (P=1,$

**Table 1**  
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



**Fig. 2.** Single-day profile of observed and forecasted PV power.

$D=0, Q=1, s=24$ , which are listed in Table 1.

To assess the implemented SARIMA model, we scrutinize its  $R^2$  and root-mean-square error, yielding values of 0.938 and  $62 \text{ W/m}^2$ , correspondingly. The observed irradiance peaks range between  $800$  and  $1000 \text{ W/m}^2$ . Consequently, the chosen model proves to be well-suited for forecasting.

Fig. 2 illustrates the contrast between the forecasted daily profile of PV power and the actual observed PV power. This analysis focuses on monocrystalline PV panels boasting a 19% efficiency. The computed PV output is derived from the predicted irradiation [21] using (1).

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

where  $\eta$  = efficiency of PV module,  
 $A_{PV}$  = PV module's surface area ( $\text{m}^2$ )  
 $G_F$  = forecasted solar irradiation ( $\text{kW/m}^2$ )  
 $T_C$  = panels' operating temperature ( $^{\circ}\text{C}$ ).

#### 3.2. EV charging demand

The parking facilities are anticipated to serve predominantly those utilizing EVs for workplace purposes. As a result, the occupancy of the parking lots is linked to the typical working hours between 9:00 a.m. and 5:00 p.m. The assumption is made that the distribution of arrival and departure times for EVs follows a normal distribution as outlined in (2).

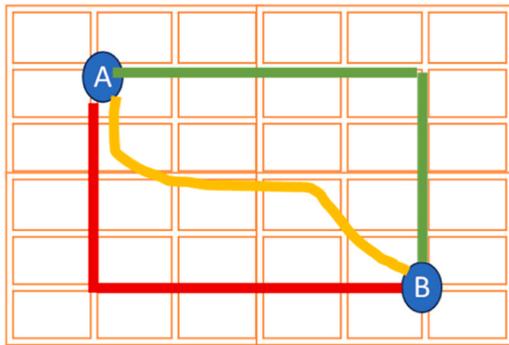
$$f(t_i) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\left[ \frac{(t_i - \mu_i)^2}{2\sigma_i^2} \right]} \quad t > 0 \quad (2)$$

**Table 2**  
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

**Table 3**  
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



**Fig. 3.** A simplified traffic model based on the Cartesian system.

where  $i = \{1, 2, \dots, N\}$  represents  $i$ th EV,  $\sigma_i$  and  $\mu_i$  are mean and standard deviation respectively. Table 2 shows the EV distribution characteristics adopted from [22].

EV fleets in Auckland include a diverse range of EV types, each equipped with batteries of varying capacities ranging from 9 to 60 kWh [23]. According to [24], workplace charging is noted for extending the range of EVs but does not fully charge them. The literature commonly represents SoC using uniform [25], normal [26] and log-normal [27] 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). The EV characteristic data is presented in Table 3

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

#### 4. Transactive energy management modelling

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

##### 4.1. 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 [28].

To model the range anxiety, it is essential to model the local transportation infrastructure, estimating battery consumption for travelling to the destination. Traditional EV travel planning models and optimal path algorithms, such as [29], 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 [30], a simple algorithm models optimal pathfinding 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. Fig. 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).

$$D_{AB} = \sqrt{|y_B - y_A|^2 + |x_B - x_A|^2} \quad (4)$$

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.

Nonetheless, roads might not adhere strictly to orthogonal patterns within actual transportation networks, and EVs may deviate from the shortest route. Consequently, introducing a normal distribution is employed to address uncertainties in driving in (5) [30].

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

where  $D_{AB}$  is actual driving distance, and  $\mu_{AB}$  is standard deviation.

##### 4.2. Electricity prices

The electricity pricing used in this research is taken from [31] 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 to 10 am and 5 pm to 7 pm in the winter season. With NZ being a winter-peaking country, winters have a higher need for EV management. Hence, the winter season is considered for analysis in this research.

##### 4.3. Range anxiety

EV drivers frequently experience range anxiety as they drive. The level of range anxiety is directly related to the driving distance of the electric vehicle and inversely related to its battery capacity. As a result, the range anxiety of an EV intending to transact energy is quantified in (6).

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

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

The EV users will be influenced by range anxiety based on the charging capacity of the vehicle. The more the range anxiety EV user has; its charging demand will be more. Hence, the charging requirements of electric vehicle (EV) users can be articulated in (7) in terms of range anxiety and the upper/lower limits of charging capacities.

$$E_{\text{Req},t} = E_{\text{Min},b} + R_{b,t} \times (E_{\text{Max},b} - E_{\text{Min},b}) \quad b \in i_{\text{buy}} \quad (7)$$

where  $E_{\text{Max},b}$  and  $E_{\text{Min},b}$  refer to maximum and minimum energy of  $b^{\text{th}}$  EV respectively.

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).

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

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

$$i_{buy} + i_{sell} = N \quad (9)$$

For each parking lot, the total available energy of a parking lot  $p$  at time  $t$  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.

$$E_{Exc_{p,t}} = \sum_{i=1}^k (E_{Exc_{s,t}} - E_{Re_{q,b,t}}) + P_{PV_{p,t}} * \Delta t_s + b = N \quad (10)$$

$$E_{Exc_{p,t}}^{avg} = \frac{E_{Exc_{p,t}}}{b} \quad (11)$$

## 5. Objective function formulation

The transactive trading mechanism is adopted from [28], where the energy valuation of each parking lot is calculated based on the required energy to buy, as shown in (12).

$$E_{val_{p,t}} = E_{Re_{q,p,t}} - E_{Exc_{p,t}}^{avg} \text{ for } p \in p_{buy} \quad (12)$$

Based on the assessed value, each purchaser submits their bid to the local trading agent, with the bid price constrained within the open set limit  $(C_{elec}, C_{FIT})$  for a feasible market structure to maintain a viable market structure. The reasoning behind this limitation is that sellers can sell surplus energy to the grid at the FIT. At the same time, buyers can acquire energy from the grid at an electricity tariff. Consequently, this limit fosters energy trading among parking lots, creating a community of energy buyers and sellers with minimal direct influence from the grid. This setup aims to ensure that the price signal from the central power station does not significantly impact the transactive trading performance, as observed in the scheduling and trading of energy in existing systems [32].

To succeed in the auction, buyers with higher valuations place bids closer to the utility tariff, while sellers with substantial negative valuations bid 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  $(C_{elec}, C_{FIT})$ .

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

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 for sellers can also be described in the same way.

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

The energy allocation by the local trading agent is determined by the bid offers received from participants. An auction-based mechanism is well-suited for assessing such trades, where participants have varying bid values based on their energy valuations. Transactions are risk-averse, excluding bids beyond the limit  $(C_{elec}, C_{FIT})$  to ensure no participant losses. The local trading agent organizes buyer bids in descending order, prioritizing those with higher energy valuations and aligning them with the seller's bid.

The double-sided auctions operate on bid submissions from multiple buyers and sellers, and the proposed bidding system, thanks to its generic formulation, remains independent of the number of participants. To achieve optimal energy allocation, an optimization problem is formulated.

$$C_{tot,b} = \left\{ \sum_{p=1}^P \sum_{t=1}^T \sum_{i=1}^N \left( \left( P_{g_{2V_{i,p,t}}} - \frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{elec} + P_{v_{2G_{i,p,t}}} * C_{deg} + (P_{PV_{2EV_{i,p,t}}} + P_{PV_{2G_{p,t}}}) * C_{PV} - \left( P_{v_{2G_{i,p,t}}} + P_{PV_{2G_{p,t}}} \right) * C_{FIT} \right) + \sum_{p=1}^P \sum_{t=1}^T \left( \frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{bid_{p,t}} \right\} * \Delta t \text{ } p \in p_{buy} \quad (15)$$

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

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

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

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

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

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

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).

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

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

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

$$x \leq b * M \quad (23)$$

where  $b$  represents the binary variable,  $c$  represents the continuous variable, and  $M$  represents a set of very large numbers. If  $b = 0$ , the variable  $x$  will also be 0 as per (20). However, if  $b = 1$ , then (23) shows a non-binding constraint. Further, Eqs. (21) and (22) will result in  $x=c$ . Accordingly,  $x$  will show either 0 or  $c$  values based on these constraints. For more details, Ref. [33] can be referred to.

### 5.1. 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 [28].

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

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

where each set is the pair of expected values and its probability,  $\rho$  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).

$$\sum_{i=1}^n \rho_{PV}^i = 1 \quad (25)$$

The previously developed cost function in (15) has been updated to incorporate uncertainties for buyers, as shown in (26). 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

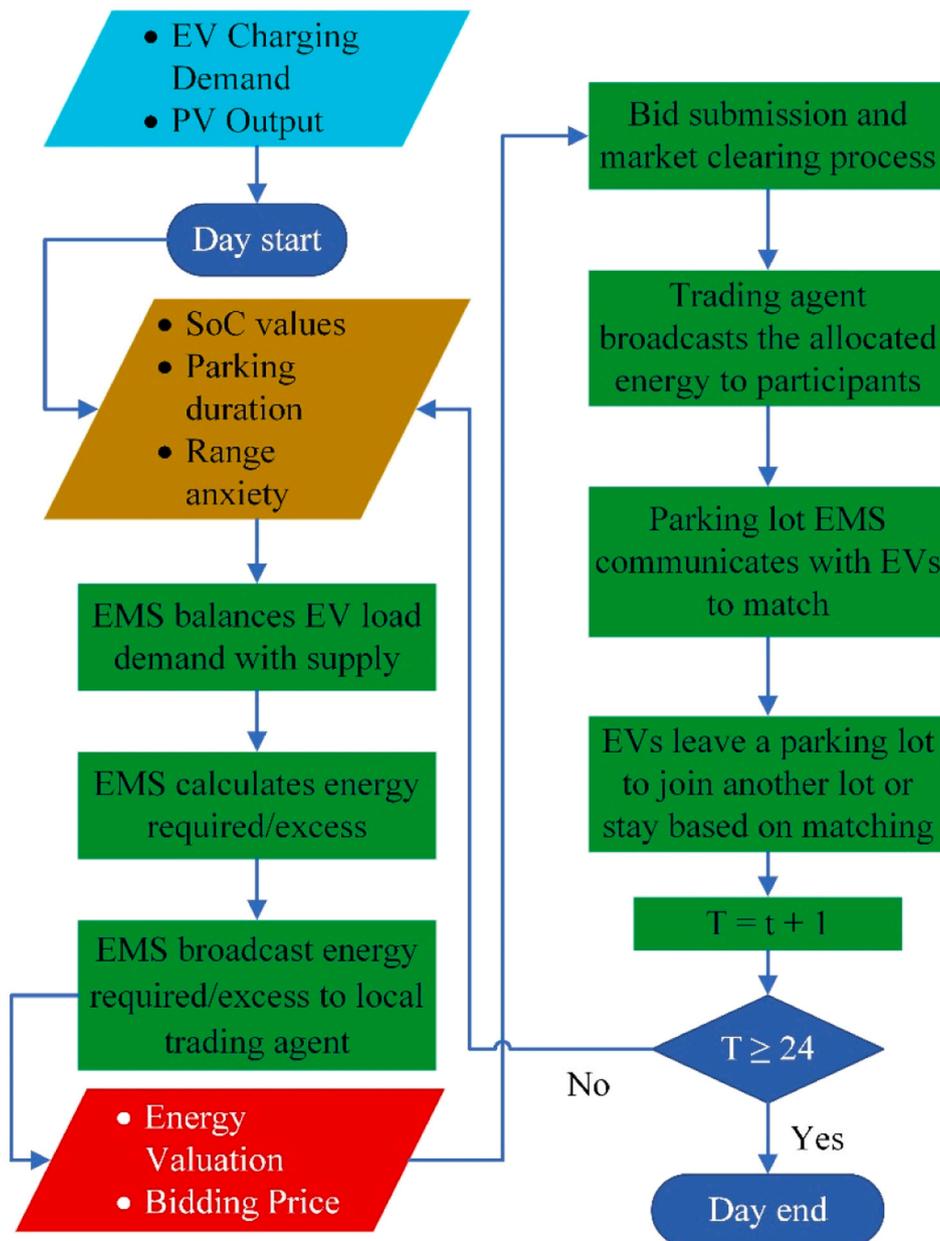
**Table 4**  
Details of Probability Distributions.

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

be required to sum up to one.

$$C_{tot,b} = \left\{ \sum_{s=1}^n \rho^s \left\{ \sum_{p=1}^P \sum_{t=1}^T \sum_{i=1}^N \left( \left( P_{g2v_{i,p,t}} - \frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{elec} + P_{v2g_{i,p,t}} * C_{deg} + (P_{PV2EV_{i,p,t}} + P_{PV2G_{p,t}}) * C_{PV} - (P_{v2g_{i,p,t}} + P_{PV2G_{p,t}}) * C_{FIT} \right) + \sum_{p=1}^P \sum_{t=1}^T \left( \frac{E_{buy_{p,t}}}{\Delta t} \right) * C_{bid_{p,t}} \right\} * \Delta t \right\} pCP_{buy} \quad (26)$$

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 also



**Fig. 4.** A flowchart of the EV management system process.

incorporating the scenario index,  $s$ , as well. The cost function for sellers can also be modified similarly before optimizing for total cost as per (16).

Five distinct, discrete probability distributions are analyzed for PV generation to examine the effects of uncertainty. The aim of utilizing various discrete distributions is to demonstrate how different degrees of uncertainty in PV generation influence 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). Five distinct scenarios were considered, with the details of the discrete probability distribution functions (values and the probability of occurrence) shown in Table 4. The expected  $x\%$  means the expected value is  $x\%$  of the forecasted value.

### 5.2. Energy management algorithm

The energy management algorithm is highlighted in the following steps and shown in the flowchart in Fig. 4:

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 offers various EV parking choices determined by factors such as location, accessible power resources, and rates for charging or discharging. The platform uses EVs' status to determine 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.
5. 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.

## 6. 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 [34]. 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 facilities, each outfitted with a 10 kWp photovoltaic (PV) system. It is assumed that 25 electric vehicles

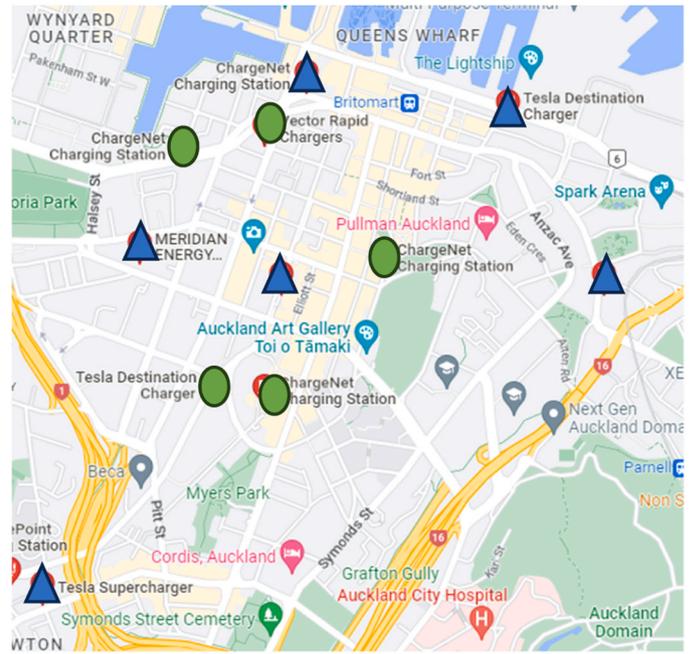


Fig. 5. Map of parking lots and public charging stations.

Table 5  
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%)

are engaging in V2G per parking facility. The analysis does not consider the auxiliary power consumption of the parking lots. Five public charging spots are considered in this paper. Fig. 5 shows the spatial locations of EV parking lots (in blue) and public charging spots (in green).

The V2G-induced expense related to battery degradation amounts to 0.065 NZ\$ per kWh, as referenced in [35]. To ensure a more realistic analysis, the energy generated by PV output is not treated as free. The LCOE for PV is set at 0.12 NZ\$ per kWh, based on information from [36]. The optimization process is conducted over a 24-hour cycle spanning from 12 a.m. to 11.59 p.m. The selected Feed-in Tariff (FIT) value is 0.08 NZ\$ per kWh [37].

The daily system cost comparison for the three cases is shown in Table 5. The daily system costs 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.

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. Fig. 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.

The availability of 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

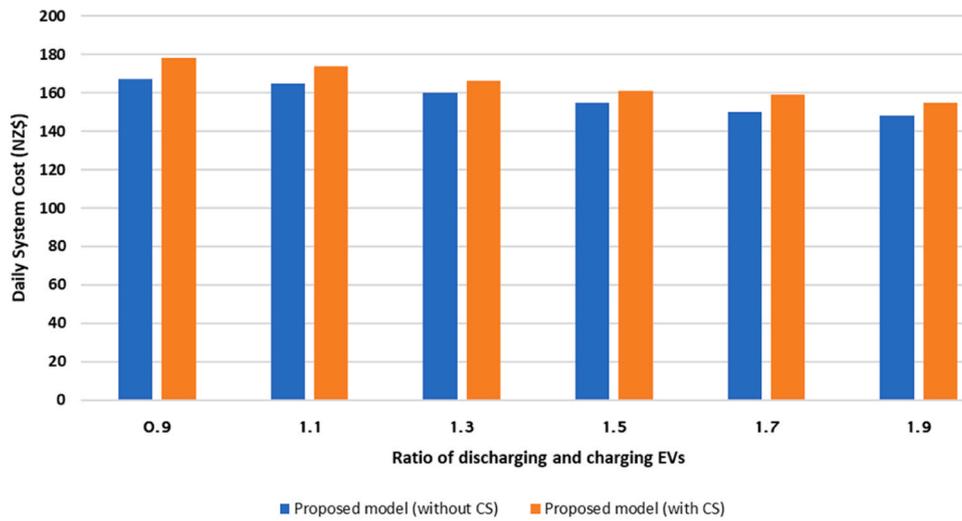


Fig. 6. Variation of system cost with respect to the number of discharging EVs.

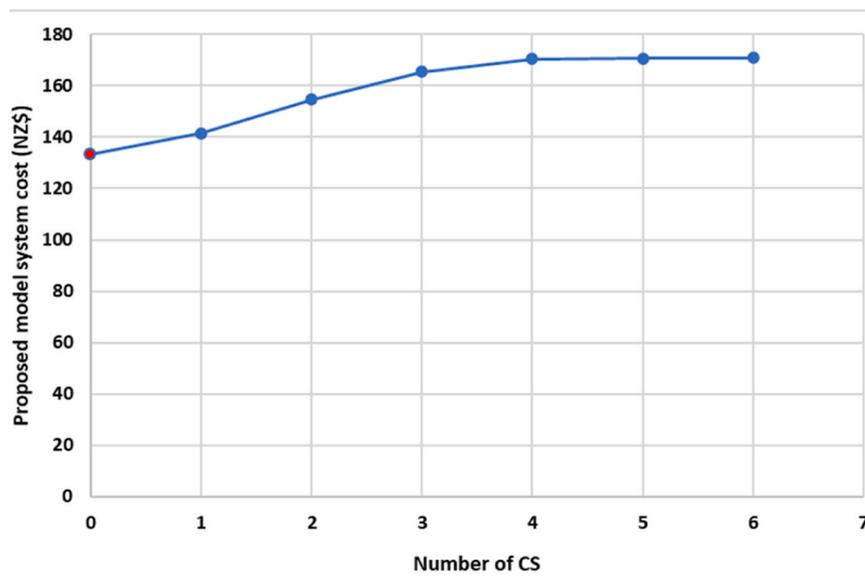


Fig. 7. Variation of system cost with number of CS.

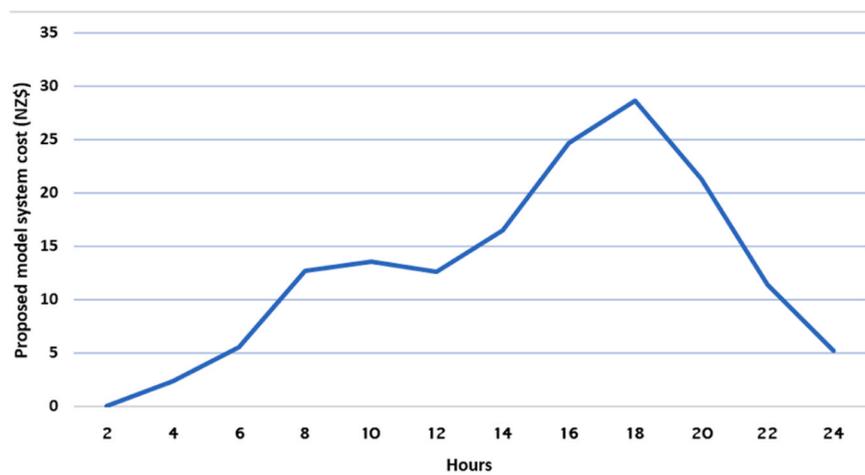


Fig. 8. Variation of system cost with time.

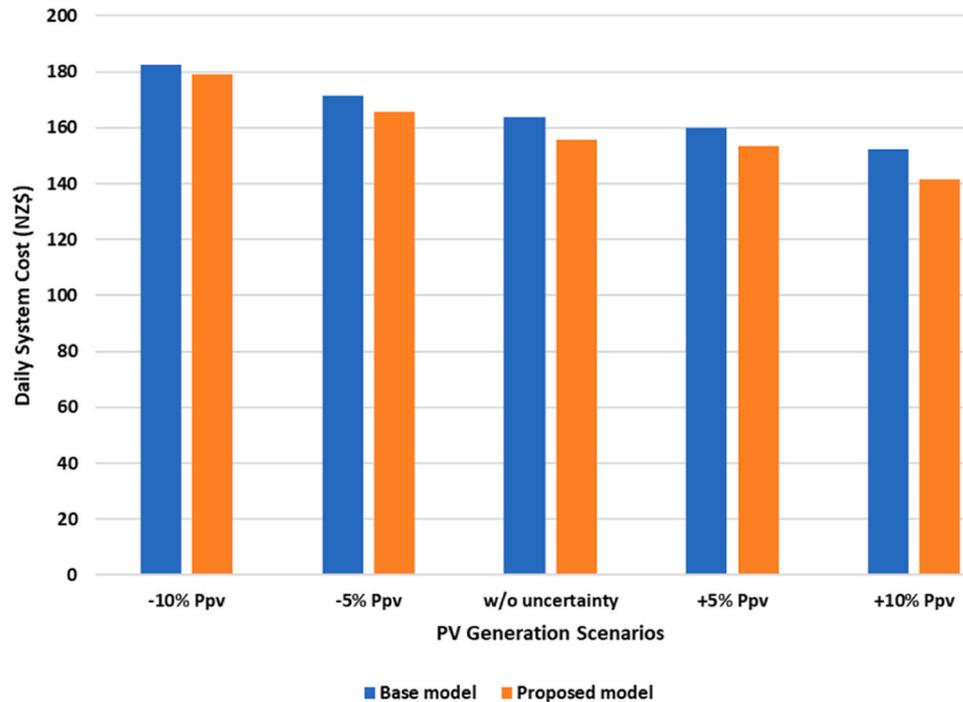


Fig. 9. System cost variation with uncertainty in PV generation.

available for transactive trading. Such scenarios will lead to public charging facility usage by range anxious EVs, albeit at a higher cost. Fig. 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.

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 Fig. 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. Fig. 8 shows the variation in system cost during the day.

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. Fig. 9 shows the variation of system cost for the base and proposed model in each of these scenarios, where Ppv refers to PV generation.

## 7. Conclusions

Range anxiety is one of the significant barriers to the implementation of transactive energy management systems for 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 3–10% 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 1–5%.

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 2% 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.

## CRediT authorship contribution statement

**Asaad Mohammad:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tek Tjing Lie:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Conceptualization. **Ramon Zamora:** Writing – review & editing, Validation, Supervision, Investigation, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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