EV scheduling framework for peak demand management in LV residential networks

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***Abstract*—Increased electrification in the residential and transport sectors is changing the energy demand profiles significantly which results in reshaped peak demand. These changes in demand profiles can cause grid overloading and jeopardize network reliability especially when the excessive use of electricity within a network is uncoordinated. In this paper a comprehensive energy management system (EMS) is proposed which schedules the optimal charging/discharging of electric vehicles (EVs) in a low voltage (LV) residential network to minimize the cost of electricity for energy consumers and manage the peak power demand to avoid overloading of the grid. The proposed EMS also accounts for uncertainties associated with the forecasts, exploits the energy storage available in EV batteries while considering the battery capacity degradation to avoid excessive charge/discharge cycles and prioritizing the preferences of energy consumers. The proposed EMS is assessed by means of simulation studies considering an LV residential neighborhood in Sydney, Australia. The results indicate the effectiveness of the proposed strategy to minimize the cost of electricity for the EV owners while managing the peak demand for the grid operators. Comparison with the state-of-the-art EV scheduling strategies indicates that the proposed strategy can improve the load factor of the local network up to 36%, the peak-to-average-ratio (PAR) up to 27%, and cost-reductions up to 56%.**

***Index Terms*—Electric Vehicle, Vehicle-to-Grid (V2G), Energy Management, Stochastic Modelling, Mixed-Integer Programming, Peak Demand Management**

I. Introduction

The energy demand in the residential sector has significantly increased in Australia and other parts of the world during the last two decades, and this trend is predicted to continue in the future [1]. Electricity is the most used energy source in the residential sector which accounts for more than 40% of household end-use [2]. Similarly, electrification of the transport sector is on the rise due to favorable regulations and technological advancements. More than 2 million plug-in electric vehicles were sold in 2019 [3].

The increase in electrification of the residential and transport sector is changing the energy demand profile significantly, thereby reshaping the peak demand on the local electricity network. This change in the peak demand profile is a threat to network operators especially when the energy consumption is uncoordinated. The increasing energy demand could either be mitigated with network capacity enhancement or by managing the load at the demand side. Demand side management (DSM) is one approach to extend grid limits somewhat further without investing too much in the network fortification [4]. Network fortification being excessively cost dependent is expected to be the last choice for most network operators. However, the DSM requires investment in terms of incentivizing the consumers, sometimes in return for compromising their freedom of using the utilities at will. Dynamic tariffs and demand response programs are introduced globally to influence responsive consumers to alter their consumption profiles. Light-duty EV owners can easily take advantage of this by scheduling their EV charging during off-peak tariff periods [5]. Thus, EV management strategies are progressively being received to increase monetary motivating forces during peak demand periods that sell energy to the grid utilizing the vehicle-to-grid (V2G) or vehicle-to-building (V2B) functionalities [6], [7].

Most light-duty EVs are normally charged at private dwellings [1] and can frequently expend the peak demand of the entire building. With such increase in electricity demand the networks can experience their capacity limits and violate operational constraints. Without significant framework fortifications, most low voltage (LV) residential distribution networks will not have the option to oblige this expanding EV charging request because of their restricted capacity limits [8]. Therefore, the localized capacity issues of increased EV integration into the distribution network require sophisticated EV management strategies [9].

The problem of scheduling charging/discharging of EVs to minimize the cost for EV owners and manage the peak load for grid operator is addressed in literature. Authors in [10] investigated the joint optimization of EVs and home energy scheduling with the objective of minimizing the total cost of electricity while considering user comfort preferences. A method for charge/discharge scheduling for an EV is implemented in [11]. A local and global optimal scheduling charging and discharging scheme of EVs is developed in [12]. A two-stage scheduling strategy for electric vehicles at large scale is proposed by [13] to reduce the negative impact of the uncontrolled charging of EVs on the grid. A method of coordinated optimal control between PV-based storage and PEV storage is developed in [14], considering the stochastic nature of solar PV generation and load demand to minimize the cost of electricity purchase. Authors in [15] mainly focused on the minimization of total energy cost and reduction of peak-to-average ratio of energy usage for multiple homes in a community. A web-based registration system that gathers

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the actual upcoming energy requirements from EV owners to schedule the charging needs is presented in [16]. An apartment-level EV charging coordination scheme is proposed by [17] to reduce the peak EV charging load and minimize the apartment-level EV charging cost.

However the proposed models in [10]–[12], [15], [17] do not account for the uncertainty associated with the errors in forecasts. Authors in [10]–[12], [14]–[16] did not model the battery capacity degradation to avoid frequent charge/discharge cycles of EV batteries while exploiting the complimentary battery storage from EVs. Authors in [12], [13], [17] did not consider the EV owners travel patterns to ensure user preferences. References [13], [16], [17] did not account for the impact of distributed energy resources on scheduling EVs. While [13] is mainly effective for large scale estimations of charge/discharge impacts of EVs on the grid.

This paper proposes a comprehensive energy management system which schedules the optimal charging/discharging of EVs in a LV residential network to minimize the cost of electricity for energy consumers and manage the peak power demand to avoid overloading of the grid. Mixed integer programming based approach is used to optimize the charge/discharge scheduling of EVs while considering all associated constraints. The error in day-ahead forecasts is compensated by stochastic approach by generating and evaluating large number of scenarios. The proposed model also accounts for battery capacity degradation to avoid insignificant charge/discharge cycles of EV batteries. Constraints are added to ensure that travel needs of EV owners are given priority rather than excessive use of EVs for V2G & V2B services. The key contributions of this paper are to:

1) design a framework for coordinated management of EVs to minimize cost for EV owners and reduce peak demand,
2) develop an energy management system which exploits the complimentary energy storage available with EVs through V2G & V2B flexibilities, while accounting for battery capacity degradation to avoid excessive charge/discharge cycles and prioritizing travel needs of EV owners,
3) design and implement a comprehensive energy management system that also accounts for the uncertainties associated with the predicted parameters

The remainder of this paper is organized as follows: the system architecture for the proposed EV management framework is presented in Section II, followed by the proposed methodology for EV management in Section III, the numerical validation and case studies are discussed in Section IV, results are presented in Section V and discussed in Section VI, while Section VII concludes this article.

II. System Architecture

The outline of the framework design for the proposed EV management strategy is shown in Figure 1. The strategy is developed for an LV residential neighborhood, wherein the aggregator does the fundamental data trades between the individual household and the grid. The aggregator can be a delegate of the grid operator or an independent third party operator.

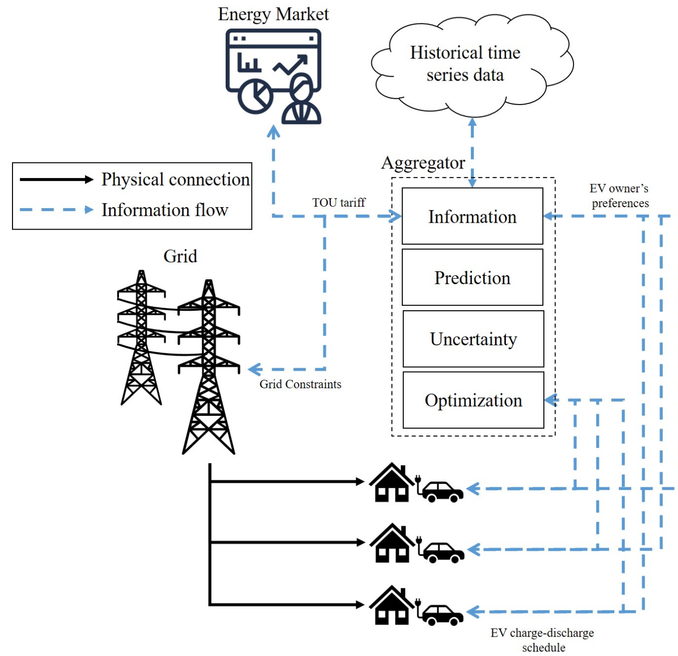

Fig. 1. System architecture of the proposed EV management framework.

EV owners send their day-ahead preferences to the aggregator. The aggregator predicts the day-ahead load profiles of all household consumers, EV owners, and weather inputs for solar PV generation based on the historical time series data-set. Despite, precise estimations for day-ahead predictions, there is still a factor of uncertainty associated with the predicted outputs. A stochastic approach is adopted to compensate for the uncertainty factor. The aggregator generates large number of scenarios for the predicted parameters and takes into account the impact of each scenario while computing the optimal schedule for EVs unlike the deterministic models, which only depend on single set of inputs for optimal scheduling.

The aggregator receives maximum demand allocation for the local network from the grid operator. This input works as a maximum capacity constraint for managing the peak demand. Based on this information, the aggregator determines the optimized charge-discharge schedules for the EVs in the network. The proposed strategy assumes that each residential neighborhood is managed by a single aggregator. Each aggregator is responsible for coordinating with the EVs within its cluster. The functionality for EV charge-discharge scheduling model is implemented on the aggregator. The aggregator receives the following information:

1) travel preferences from EV owners
2) household load preferences from household owners
3) TOU tariff structure from the market
4) maximum demand limits from the grid

In addition, the aggregator has access to the historical time-series data-set of connected load, EV users travel patterns, and solar PV generation to make predictions for day-ahead scheduling. The aggregator predicts day-ahead household load, solar PV generation, and EV availability based on historical time-series data-sets. Then the aggregator determines the uncertainty factor based on the proposed stochastic model. The aggregator then dispatches the charge-discharge scheduling of EVs based on mixed-integer programming model subject to grid constraints. The aggregators assumed in this paper do not take part in the energy market. The aggregators just deal with the local EV flexibilities and provide grid support services; therefore, the competition among aggregators is past the extent of this article.

III. EV Scheduling Model

The proposed EV management system schedules the charge-discharge of EVs in day-ahead stages and determines the demand and supply to minimize the energy cost. The proposed system predicts the household load, expected solar generation and EV availability in the first stage.

As the scheduling is determined in the day-ahead stage, different sources can contribute towards uncertainty. In this article we consider inflexible household load demand, on-site solar generation and EV travel profiles as the sources of uncertainty. In the second stage the uncertainty model accounts for the errors associated with day-ahead predictions which may lead to the un-optimized scheduling decisions.

Once the model have the adjusted predictions incorporated with the processed uncertainties, the model process the given predictions to produce an optimized schedule of EV charge-discharge while considering the constraints.

A. Prediction Model

An artificial neural networks (ANN)-based prediction model is used in this paper that forecasts household load, solar PV generation and EV availability from historical time-series dataset considering seasonal (i.e. summer, winter, autumn, and spring) and daily (i.e. week-days and weekends) variations. ANN is a reliable forecasting method in many applications including forecasting of household load, wind speed and weather [18]. A back-propagation learning algorithms is used in this paper which is commonly used algorithm in the feed-forward ANN. The forecast values, $\mathbb{Z}^{d,s}_{(t,h)} \in \{\mathbb{D}^{d}_{(t,h)}, \mathbb{A}^{d}_{(t,h)}, \mathbb{X}^{d,s}_{(t,h)}\}$, can be expressed as:

$$\mathbb{Z}^{d,s}_{(t,h)} = \sum_{j=1}^{n} \delta_j f\left(\omega_{0j} + \sum_{i=1}^{x} \omega_{ij} \mathbb{Z}^{d,s}_{t-i,h}\right) + \varrho_t + \delta_0 \quad (1)$$

where n is the number of hidden layers in the ANN model, the weights from the layers are indicated by ω_{ij} and δ_j . The ϱ_t is a random shock, where ω_{0j} and δ_0 represent the bias terms of the ANN. The superscripts d represents the type of the day and s represents the season of the year. The subscripts t & h represents the time of day and the individual household respectively.

B. Stochastic scenario generation of uncertain variable

The EV charge-discharge schedule is determined in the day-ahead stage, therefore different sources can contribute towards uncertainty. Only the variables which can have high impact on the decision-making for EV charge-discharge scheduling are considered. The uncertainty modelling and scenario generation of these variables are discussed in the following subsections.

1) Household load demand and PV generation: Household load and solar PV generation vary from day to day (i.e. week-day/weekend) and from season to season (i.e. summer/autumn/winter/spring). Considering the seasonal and daily variations, the probability distributions functions (PDFs) of the historical time series data for household load and solar PV generation are first estimated. Then, stochastic scenarios of the uncertain variables, $\mathbb{X}^{d,s}_{(t,h)} \in \{\mathbb{L}^{d,s}_{(t,h)}, \mathbb{K}^{s}_{(t,h)}\}$ are generated using the following models.

$$\begin{aligned}\mathbb{X}^{d,s}_{(t,h)} &= f\left((t,h)|_{d,s} \| \mu^{d,s}_{(t,h)}, \sigma^{d,s}_{(t,h)}\right)\\ &= \frac{1}{\sigma^{d,s}_{(t,h)}\sqrt{2\pi}} e^{\left(\frac{-\left((t,h)|_{d,s} - \mu^{d,s}_{(t,h)}\right)^2}{2(\sigma^{d,s}_{(t,h)})^2}\right)}\end{aligned} \quad (2)$$

where $\mu^{d,s}_{(t,h)}$ and $\sigma^{d,s}_{(t,h)}$ represent the mean and standard deviation of the historical data, respectively. Here t is the time of day, d is the day of the week, and s is the season of the year. $\mathbb{X}^{d,s}_{(t,h)} \in \{\mathbb{L}^{d,s}_{(t,h)}, \mathbb{K}^{s}_{(t,h)}\}$ represent the uncertain variables, i.e. household load and PV generations.

2) EV Availability: Similar to load demand and PV generation, the vehicle travel pattern varies from day to day and from season to season. Therefore, the historical time series data for EV travel patterns is used to extract the probability distribution functions (PDFs) for EV availability, travel distance, and range efficiencies. The availability is the binary variable that indicates if an EV is at home for charging or discharging, i.e. it is 0 when EV is away and 1 when an EV is at home. From the PDF of EV availability according to historical data, the availability of a particular EV at time t and day of the week d, can be estimated as:

$$\begin{aligned}\mathbb{A}^{d}_{(t,h)} &= f\left((t,h)|_{d} \| \mathbb{N}^{d}_{(t,h)}, p^{d}_{(t,h)}\right)\\ &= \binom{\mathbb{N}^{d}_{(t,h)}}{p^{d}_{(t,h)}} p^{d}_{(t,h)} (1 - p^{d}_{(t,h)})^{(\mathbb{N}^{d}_{(t,h)} - (t,h)|_{d})}\end{aligned} \quad (3)$$

where $\mathbb{N}^{d}_{(t,h)}$ represents the number of scenarios for each EV to estimate the availability of an EV at home for charging/discharging and $p^{d}_{(t,h)}$ is the success probability of the scenario.

Once the availability is estimated in a scenario, the status of the EV in that scenario is then calculated. Four EV statuses have been identified for the proposed EV management model: available, not available, departed, and arrived. The EV status is calculated according to Algorithm 1, which identifies when a particular EV arrives home or departs from home to assign corresponding statuses.

3) EV travel and range efficiency: The actual range of an EV can differ substantially in real-life situations and can be much shorter than the figures given by the manufacturers [19]. Therefore, instead of using a constant number for EV efficiency, the proposed method incorporates the uncertainty associated to the range efficiencies of the EV. This paper considers the seasonal effect on the efficiency and modelled the different range of efficiencies for summer and winter. The EV efficiency and daily commute distance of EV for scenario

Algorithm 1 Status Matrix

for $t \in \mathbb{T}$ **do**
  for $h \in \mathbb{H}$ **do**
    for $i \in \mathbb{I}$ **do**
      for $d \in weekday, weekend$ **do**
        if $\mathbb{A}^{d}_{(t,h,i)} = 1$ **then**
          $\mathbb{S}^{d}_{(t,h,i)} = 1$ ▷ available
        else if $\left(1 - \mathbb{A}^{d}_{(t,h,i)}\right) = 1$ **then**
          $\mathbb{S}^{d}_{(t,h,i)} = 4$ ▷ departed
        else
          $\mathbb{S}^{d}_{(t,h,i)} = 3$ ▷ arrived
          $\mathbb{S}^{d}_{(t,h,i)} = 2$ ▷ not available
end procedure

generation are estimated based on Eq. (4) from the historical time series data-set.

$$\mathbb{J}^{d,s}_{(t,h)} = f\left((t,h)|_{d,s} \| \mu^{d,s}_{(t,h)}\right) = \frac{1}{\mu^{d,s}_{(t,h)}} e^{\left(\frac{-(t,h)|_{d,s}}{\mu^{d,s}_{(t,h)}}\right)} \tag{4}$$

where $\mathbb{J}^{d,s}_{(t,h)} \in \{\mathbb{D}^{d}_{(t,h)}, \mathbb{E}^{s}_{(t)}\}$. The mean distance traveled and the mean efficiency of an EV are represented by $\mu^{d}_{(t,h)}$ respectively. The superscripts d & s represents the day of the week and seasonal inputs respectively.

C. Uncertainty Modelling

Large number of scenarios are generated for the parameters with high uncertainty. These scenarios are generated based on historical time series data. The uncertainty factor could be due to human behavior or unpredictable weather conditions. These parameters include household load $\mathbb{L}^{d,s}_{(t,h,i)}$, solar generation $\mathbb{K}^{s}_{(t,h,i)}$, EV availability $\mathbb{A}^{d}_{(t,h,i)}$ at home for charging/discharging operations, distance traveled $\mathbb{D}^{d}_{(t,h,i)}$ by EV owners when they are away from home and efficiency of EVs $\mathbb{E}^{s}_{(h,i)}$. Here the subscripts t, h & i represent the time of day, the household and the scenarios, respectively. The superscripts d & s represents the day of the week and the season of the year respectively.

These scenarios are fed into the optimization model explained in Section III-D. The optimization model evaluates the impact of each scenario on the scheduling of EVs for each household as defined in Eqs. (5) to (8). The charge/discharge scheduling of EVs are computed based on equally weighted probabilities of each scenario. The proposed EMS minimize the aggregated cost of electricity for the aggregator while considering the impact of large number of possible scenarios instead of evaluating the EV schedule based on deterministic input parameters.

D. Optimization Model

The objective function is designed to minimize the aggregated cost of electricity for the aggregator. It is the aggregated sum of the cost of electricity for each household. The aggregated cost for each household is composed of the cost of electricity traded between the grid and respective household along with the costs of battery capacity degradation for EVs as a result of charge/discharge cycles. battery capacity degradation is explained in Equations (23) and (24). The details of energy transactions and optimization constraints are mathematically modelled in Equations (5) to (14) and (17) to (22).

$$TC = \min \sum_{t \in \mathbb{T}} \sum_{h \in \mathbb{H}} (HC_{t,h}) \tag{5}$$

$$HC_{(t,h)} = EB_{t,h} + ES_{t,h} + BD_{t,h} \tag{6}$$

$$EB_{(t,h)} = \sum_{i \in \mathbb{I}} \frac{1}{\rho_i} \left(\alpha_{(t,h,i)} \mathbb{P}^{\mathbb{G}}_{(t,h,i)} \Delta t \Psi^{+}_{t}\right) \tag{7}$$

$$ES_{(t,h)} = \sum_{i \in \mathbb{I}} \frac{1}{\rho_i} \left(\beta_{(t,h,i)} \mathbb{P}^{\mathbb{G}}_{(t,h,i)} \Delta t \Psi^{-}_{t}\right) \tag{8}$$

$$BD_{(t,h)} = \sum_{i \in \mathbb{I}} \frac{1}{\rho_i} \left(\mathbb{C}^{\mathbb{V}}_{(t,h,i)}\right) \tag{9}$$

$$\alpha_{(t,h,i)} + \beta_{(t,h,i)} = 1 \tag{10}$$

$$\alpha_{(t,h,i)} \beta_{(t,h,i)} = 0 \tag{11}$$

$$\alpha_{(t,h,i)} \mathbb{P}^{\mathbb{G}}_{(t,h,i)} \geq 0 \tag{12}$$

$$\beta_{(t,h,i)} \mathbb{P}^{\mathbb{G}}_{(t,h,i)} \leq 0 \tag{13}$$

where the subscripts t represents the time of day, h represents the specific household & i represents a specific scenario for predicted parameters. $HC_{t,h}$ is the cost of electricity for each household, $EB_{t,h}$ is the cost of energy bought by each household, $ES_{t,h}$ is the cost of energy sold by each household and $BD_{t,h}$ is the cost of battery capacity degradation of each EV. $\mathbb{P}^{\mathbb{G}}_{(t,h,i)}$ is the power traded by each household with the grid. The objective function is designed to minimize the total cost TC, considering the associated constraints for each household. The general sign convention used for $\mathbb{P}^{\mathbb{G}}_{(t,h,i)}$ i.e. the power transactions between the grid and household are:

- Power drawn by the consumer from grid is treated positive at the rate of Ψ^{+}_{t} \$/kWh
- Power supplied back to the grid by consumer is treated negative at the rate of Ψ^{-}_{t} \$/kWh

$\alpha_{(t,h,i)}$ and $\beta_{(t,h,i)}$ are the auxiliary variables indicating the power drawn from the grid and power supplied back to the grid respectively. Eqs. (10) to (13) are the constraints to optimize the power drawn by individual household from the grid. The power balance equation for each household is presented in Eq. (14).

$$\mathbb{P}^{\mathbb{G}}_{(t,h,i)} = \mathbb{P}^{\mathbb{L}}_{(t,h,i)} + \mathbb{P}^{\mathbb{V}}_{(t,h,i)} - \mathbb{P}^{\mathbb{K}}_{(t,h,i)} \tag{14}$$

where, $\mathbb{P}^{\mathbb{L}}_{(t,h,i)}$ is the household load, $\mathbb{P}^{\mathbb{V}}_{(t,h,i)}$ is the charging/discharging power of EV and $\mathbb{P}^{\mathbb{K}}_{(t,h,i)}$ is the power generation from solar PV. When $\mathbb{P}^{\mathbb{G}}_{(t,h,i)}$ is positive, the values of auxiliary variables are: $\alpha = 1$ and $\beta = 0$, in this situation the consumer draws power from the grid. In other case, when the system has excess energy i.e. $\mathbb{P}^{\mathbb{G}}_{(t,h,i)}$ is negative, the system feeds back power to the grid. The model has the flexibility to apply different energy transaction rates for energy sale/purchase. Similarly, $\mathbb{P}^{\mathbb{V}}_{(t,h,i)}$ is positive when the EV of respective household charges and negative when discharging.

A constraint for maximum aggregated power drawn by all consumers from the grid i.e. $\overline{\mathbb{P}^{\mathbb{G}}}$, is set to manage the peak demand from grid's perspective while minimizing the cost of energy consumption for the individual consumers. Another constraint applied to the proposed EMS i.e. $\overline{\mathbb{P}^{\mathbb{V}}}$, limits the maximum aggregated power due to charging/discharging of EVs at any given time. This constraint is worked out such that the network capacity limits provided by the grid operator are never exceeded.

$$\sum_{h\in\mathbb{H}} \mathbb{P}^{\mathbb{G}}_{(t,h,i)} \leq \overline{\mathbb{P}^{\mathbb{G}}} \tag{15}$$

$$\sum_{h\in\mathbb{H}} \mathbb{P}^{\mathbb{V}}_{(t,h,i)} \leq \overline{\mathbb{P}^{\mathbb{V}}} \tag{16}$$

The state of charge of EV batteries is modelled in Eq. (17). The model considers the lower and upper bounds of battery state of charge to optimize the effective battery life Eqs. (20) and (21). The model also has the flexibility to prioritize the travel needs of the consumers Eq. (22).

$$\delta^{\mathbb{V}}_{(t,h,i)} = \delta^{\mathbb{V}}_{(t-1,h,i)} + \frac{\mathbb{A}^{d}_{(t,h,i)} \eta^{\mathbb{V}}_{h} \mathbb{P}^{\mathbb{V}}_{(t,h,i)}}{\hat{\mathbb{P}}^{\mathbb{V}}_{h}} \tag{17}$$

$$\mathbb{P}^{\mathbb{V}_{dis}}_{\Uparrow} \leq \mathbb{P}^{\mathbb{V}}_{(t,h,i)} \leq \mathbb{P}^{\mathbb{V}_{chg}}_{\Uparrow} \tag{18}$$

$$\mathbb{P}^{\partial}_{(t,h,i)} = \frac{\mathbb{E}_{(h,i)} \mathbb{D}^{d}_{(t,h,i)}}{\hat{\mathbb{P}}^{\mathbb{V}}_{h}} \tag{19}$$

$$\delta^{\mathbb{V}}_{(t,h,i)} \geq \delta^{\mathbb{V}}_{\Downarrow} \tag{20}$$

$$\delta^{\mathbb{V}}_{(t,h,i)} \leq \delta^{\mathbb{V}}_{\Uparrow} \tag{21}$$

$$\delta^{\mathbb{V}}_{(t,h,i)} \geq \mathbb{P}^{\partial}_{(t,h,i)} \tag{22}$$

where $\mathbb{P}^{\mathbb{V}_{chg}}_{\Uparrow}$ & $\mathbb{P}^{\mathbb{V}_{dis}}_{\Uparrow}$ represents the maximum charging and discharging power limits for EVs. $\mathbb{A}^{d}_{(t,h,i)}$ is the availability of an EV at home for charging/discharging and $\mathbb{D}^{d}_{(t,h,i)}$ is the distance traveled by an EV at any given time t on a given day of the week d and scenario i.

The battery capacity degradation as a function of charging-discharging power is estimated based on the work done by authors in [20] and is replicated in Eq. (23).

$$\Pi_{\mathbb{P}^{\mathbb{V}}} = (\gamma_1 \upsilon + \gamma_3 \upsilon^2 + \gamma_5 \upsilon^3 + \gamma_7 \upsilon^4) + (\gamma_2 + \gamma_6 \upsilon)|\mathbb{P}^{\mathbb{V}}| + \frac{\gamma_4}{\upsilon}|\mathbb{P}^{\mathbb{V}}|^2 \tag{23}$$

$$\mathbb{C}^{\mathbb{V}}_{(t,h,i)} = \left(\mathbb{A}^{d}_{(t,h,i)} \Pi_{\mathbb{P}^{\mathbb{V}}} \theta\right) \tag{24}$$

Respective cost of battery capacity degradation is modelled in Eqs. (23) and (24) for stationary battery storage and the EV battery. Here $\Pi_{\mathbb{P}^{\mathbb{V}}}$ represents the battery capacity degradation in kWh θ is the cost of battery degradation in \$/Wh, υ is the battery voltage and γ is the battery degradation coefficient.

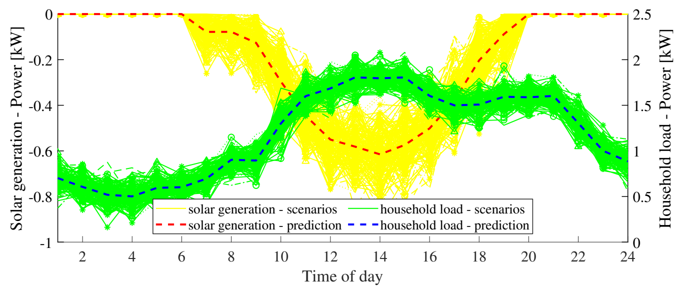

Fig. 2. Input parameters for the model.

IV. Numerical Validation

This segment discusses the simulation studies to validate the adequacy of the proposed strategy for grid support services while fulfilling consumer preferences for EV charging.

A. Simulation Setup

The proposed EV management strategy is assessed by means of simulation on an LV residential network in Sydney, Australia. The system supplies power to 175 segregated private dwellings. It is considered that around one-third (50 out of 175) of the houses in the network are equipped with EVs having V2G abilities and consent to participate in the grid support services. The maximum power supply capacity for the feeder is considered as 350 kW.

The prediction model generates day-ahead household load, solar generation Fig. 2 and EV travel patterns for 175 households. For validation of maximum peak demand, only the results of summer weekend and winter week-day are presented. The prediction model uses a 3 layered feed-forward neural network trained by the Levenberg-Marquardt algorithm. It was initiated with five neurons in the hidden layer and repeated by increasing the neurons up to 40. The best results were produced at 20 neurons in the hidden layer which is used for getting the forecasts. The historical data which is used by the prediction model, is divided into three subsets; the training set, the validating set and the testing set. 70% of the total dataset was allocated for training the model and the remaining 30% was equally divided for validation and testing purposes.

TABLE I
Tariff Parameters.

Tariff periods	TOU tariff	Feed-in tariff
Peak (2PM–8PM)	0.548 \$AU	0.107 \$AU
Off-peak (10PM–7AM)	0.149 \$AU	0.085 \$AU
Shoulder (7AM–2PM, 8PM–10PM)	0.246 \$AU	0.102 \$AU

The proposed strategy is developed using general algebraic modelling system (GAMS) and MATLAB. The EV travel patterns are modelled in MATLAB. The optimization problem in Eqs. (5) to (24) is formulated in the GAMS and solved using a commercially available solver i.e. Baron [21], with an absolute and relative optimality gap of zero. The simulation was setup on an Intel Core i7 2.00 GHz computer with 16 GB RAM. Data exchange (GDX) is used for communications between MATLAB and GAMS. The MATLAB neural

TABLE II
EV SCHEDULING STRATEGIES SETUP.

Scheduling Strategies	Uncoordinated		Decentralized				Aggregated			
	Strategy-1	Base(w/o EVs)	Strategy-2	Strategy-3	Strategy-4	Strategy-5	Strategy-6	Strategy-7	Strategy-8	Proposed
Constrained Power			✓		✓			✓		✓
Uncertainty Estimation			✓	✓			✓			✓

network toolbox (nntool) has been used to train the feed-forward ANNs. MATLAB provides builtin transfer functions that have been used for the hidden and output layers as follows: hyperbolic tangent sigmoid (tansig) for the hidden neurons; a pure linear function (purelin) for the output neurons [18].

For simplicity, we have considered a mid-range V2G capable EV with a rated battery capacity of 24 kWh and a usable battery capacity of 19.2 kWh (i.e. 80% depth of discharge), as in [22], [23]. To model the continuity, the final SoC requirements at the end of the day is considered the same as the initial SoC at the beginning of the day. The time of use tariff (TOU) and the feed-in-tariff are taken from [22], [23] are presented in Table I.

B. EV Scheduling Strategies

In light of the inputs discussed in the previous sections, the numerical simulations are conducted for the proposed EV management strategy. Likewise, to compare the effectiveness of the proposed strategy, the outcomes are compared with the accompanying cutting edge EV management strategies defined in Table II. The strategies mainly differ in either of the three main features:

- the strategies are either *Aggregated* (strategy-6, strategy-7, strategy-8 and proposed strategy) or *Decentralized* (strategy-2, strategy-3, strategy-4 and strategy-5)
- the strategies either *Include the grid capacity constraint* (strategy-2, strategy-4, strategy-7 and proposed strategy) or *Exclude the grid capacity constraint* (strategy-3, strategy-5, strategy-6 and strategy-8)
- the strategies either *Include the uncertainty estimation* (strategy-2, strategy-3, strategy-6 and proposed strategy) or *Exclude the uncertainty estimation* (strategy-4, strategy-5, strategy-7 and strategy-8)

V. RESULTS

Based on the input data, the aggregator assesses the needs of individual household and creates a day-ahead optimization schedule to minimize the cost for individual households and reduce the peak demand for the grid. the results are presented for both summer and winter to validate that the model is effective for a wide range of inputs.

A. Effect of EV scheduling on Peak Demand

The comparison of aggregated load profiles for all the strategies discussed above are presented in Figs. 3 and 4 respectively for summer and winter. The figure compares the effectiveness of the proposed method with the other EV scheduling strategies for grid overloading mitigation. It can be seen that the aggregated peak demand remains below the grid constraint set by the grid operator for all the strategies where grid constraint is applicable (i.e. proposed strategy, strategy-2, strategy-4 and strategy-7). For other strategies where aggregated peak demand constraint was not applied, the aggregated peak demand exceeds the maximum grid capacity limits. Higher demand is seen during the winter week-day compared to summer weekend due to number of vehicles returning home from work and plugging in to charge upon arrival. Whereas, on summer weekend most EVs return home in the later hours of the evening and plug-in to recharge.

In the case of uncoordinated scheduling i.e. strategy-1, the aggregated demand exceeds the maximum capacity in the evening, as almost all the EVs arrive at home and start charging during evening hours. It can also be noticed that the aggregated demand exceeds the maximum capacity during off-peak hours for the decentralized scheduling strategy. This is the rebound effect, as most of the EVs in the decentralized scheduling system do not charge in the peak-load hours due to high TOU tariff rates and they start charging as soon as the TOU tariff is reduced. Hence shifting the peak demand

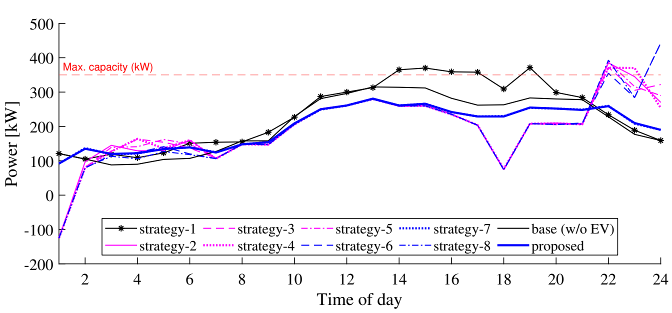

Fig. 3. Aggregated load profile (winter).

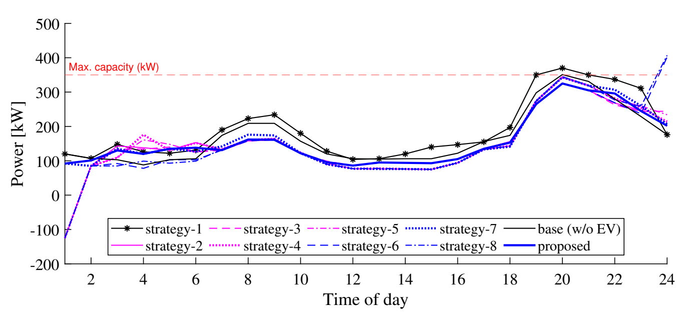

Fig. 4. Aggregated load profile (summer).

from conventional peak hours to off-peak hours. On the other hand, due to the coordinated EV management of the proposed method, the aggregated demand always stays below the maximum capacity utilizing the EV flexibilities. It also falls below the EV charging excluded aggregated demand (w/o EV case in the figure) as a portion of the load demand is also supplied via V2G and V2B of the EVs thereby reducing the overall demand on the grid, especially during peak tariff periods.

In the case of uncoordinated scheduling, for example: strategy-1, the aggregated power demand surpasses the maximum capacity limit in the evening, as practically all the EVs show up at home and begin charging during evening hours. It can likewise be seen that the aggregated power demand exceeds the maximum capacity limit during the off-peak hours for the decentralized scheduling strategy. This is the bounce back impact, as the majority of the EVs in the decentralized scheduling system does not charge in the peak load hours because of the high TOU tariff rates and they begin charging when the TOU tariff is decreased. Subsequently, shifting the peak demand from usual peak hours to the off-peak hours. On the other hand, because of the coordinated EV management of the proposed strategy, the aggregated power demand always remains below the maximum capacity limit by utilizing the EV flexibilities. It also falls below the EV charging excluded aggregated demand (i.e. w/o EV case in Figs. 3 and 4) as a portion of the load demand is also supplied via V2G and V2B, thereby reducing the overall demand on the grid, especially during the peak tariff periods.

It can be seen in Fig. 5 that the aggregated peak demand of the proposed strategy remains below the defined grid maximum constraint. However, exact like comparison of the proposed scheduling strategy with the decentralized scheduling i.e. strategy-2, shows that the maximum aggregated peak constraint is violated in winter. This is because the maximum power constraint for strategy-2 is set on individual households with EV. Therefore, individual maximum power limits are met for each household but aggregated the aggregated peak demand constraint is violated in the decentralized strategy.

B. Effect of EV scheduling on grid impact assessment parameters

At a high level, the impact of grid is monitored based on the indices called load factor (LF) and peak-to-average power ratio (PAR). Table III compares the LF and PAR of the proposed method with the other EV scheduling strategies. It can be noted that the LF and PAR for the proposed scheduling strategy are better than all the other strategies except strategy-1 in summer. Although, the LF and PAR of strategy-1 are better than the proposed strategy, but the aggregated cost of strategy-1 is significantly higher. The cost comparison is shown in Fig. 6. The LF and PAR of the proposed strategy and the like-for-like comparison i.e. strategy-2, is almost equal in summer. However, the LF of the proposed strategy is 36% higher than strategy-2 in winter and the PAR of the proposed strategy is 27% lower than strategy-2 in winter.

C. Effect of EV scheduling on cost of electricity

The aggregated costs of electricity for all the strategies are presented in Fig. 6. It can be seen that all the strategies reduce the cost of electricity compared to the uncoordinated strategy. The decentralized scheduling strategy i.e. strategy-2, appears to be the best in terms of reducing the total cost of electricity, even better than the proposed strategy. Strategy-2 reduces the cost of electricity by 57% in summer and 66% in winter compared to strategy-1 (i.e. the uncoordinated strategy). Whereas, the proposed strategy reduced the cost by 53% and 56% respectively for summer and winter compared to the uncoordinated strategy-1.

The decentralized scheduling strategy, i.e. strategies 2 to 5, shifts the EV charging from peak load periods to off-peak load hours. The proposed EV management strategy likewise offers critical cost savings contrasted with uncoordinated scheduling strategies for all the EV owners. However, the decentralized scheduling strategy performs better than the proposed strategy as far as cost savings are concerned. This is on the grounds that the proposed strategy minimizes the energy cost while complying with the grid constraints, which keeps a portion of the EVs from charging during off-peak periods as it would prompt over-loading circumstances. Despite the fact that a particular TOU tariff is utilized for validation, similar outcomes are expected for various tariff structures used in the energy markets far and wide.

Therefore, EV owners should be offered attractive incentives that urge them to take interest in such grid support services regardless of the tariff structure. However, from the grid operator's point of view, it would be financially doable to offer the EV owners the expected cost savings they would

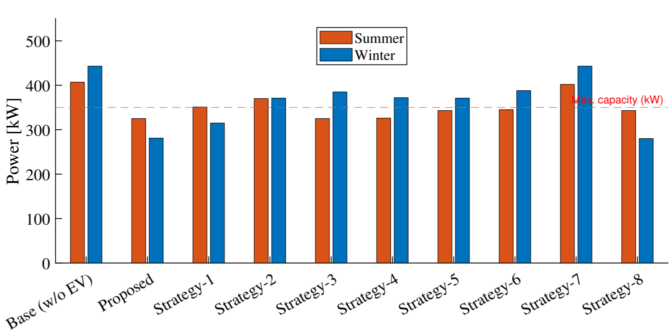

Fig. 5. Peak demand comparison of all strategies.

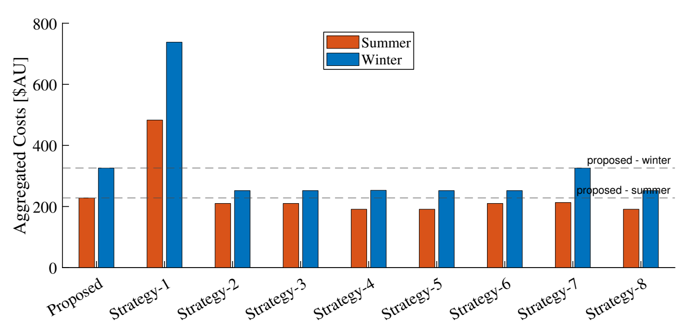

Fig. 6. Aggregated cost comparison of all strategies.

TABLE III
GRID IMPACT ASSESSMENT PARAMETERS.

Evaluation Criteria	Season	Scheduling Strategies									
		Strategy-1	Strategy-2	Strategy-3	Strategy-4	Strategy-5	Strategy-6	Strategy-7	Strategy-8	Base(w/o EVs)	Proposed
LF	Summer	0.51	0.49	0.49	0.46	0.46	0.40	0.46	0.39	0.48	0.49
PAR	Summer	1.94	2.04	2.05	2.16	2.17	2.53	2.18	2.56	2.09	2.06
LF	Winter	0.63	0.52	0.54	0.54	0.52	0.46	0.72	0.46	0.66	0.71
PAR	Winter	1.58	1.91	1.84	1.84	1.92	2.19	1.40	2.20	1.51	1.40

achieve by opting for optimized EV charging. The other option and convenient solution to address grid capacity issues (particularly for LV network) are to put resources into network fortification. Economic feasibility analysis in [24] shows that incentivizing the EV owners for their flexibility would be a significantly more prudent alternative than putting resources into the network fortifications. Therefore, using DSM adaptability to address grid capacity issues is valuable for both stakeholders i.e. the consumer and the grid.

D. Effect of EV penetration on performance

The penetration levels of EVs can seriously influence the network loading conditions and this can affect the exhibition of the proposed EV management strategy for grid support services. Consequently, three contextual analyses are conducted to assess the effectiveness of the proposed strategy with various penetration levels of EVs in the network. In case 1 around one-third (50 out of 175) of the houses have EVs, which is equivalent to the outcomes discussed in the previous sections. In case 2 around two-third (120 out of 175) EV penetration is considered, while case 3 considers that all houses have EVs (i.e. 100% penetration). The travel patterns, charge-discharge efficiencies and SoC requirements are selected according to Section IV-B.

The aggregated load profiles for the network in all cases are shown in Fig. 7. The aggregated peak demand of the proposed strategy remains blow the maximum capacity constraint set by the grid in all cases. It can also be noted that if the EV owners adopt uncoordinated charging strategy, it will result in challenging the grid capacity constraint even for case-1 (i.e. one third EV penetration).

The distributions of the EV owners' daily electricity costs for all cases are illustrated by the box plots in Fig. 8. It can be noted that the median cost of electricity for EV owners remains almost same except for slight variations, regardless of the EV penetration level. However, the maximum cost of the EV owners are higher as the EV penetration increase.

This is because more EVs in the network create energy demand, and while the system constraints are in place, the aggregated peak demand cannot exceed the peak demand constraint, therefore access energy is drawn from EVs in the neighborhood using the V2G flexibilities. Excessive charge-discharge of EV batteries can lead to battery degradation and its cost is incorporated in the proposed strategy. However, appropriate financial incentive packages are required to encourage EV owners' participation in the grid support functions. In addition, attractive incentives are also essential to ensure sufficient participation from the EV owners with adequate flexibility to address critical grid issues [25].

E. Effect of uncertainty modelling on performance

The proposed model accounted for uncertainties associated with the predicted parameters which is missing in [10]–[12], [15], [17]. The uncertainty associated with the predicted parameters can cause significant variations in the computed cost savings for the aggregator. The performance of the uncertainty model proposed in this article is evaluated using a case study. The aggregated cost of electricity for the proposed model is computed while considering large number of possible scenarios for each predicted parameter i.e. household load, solar generation, EV availability, distance traveled by EV when it is not available and the efficiency of EVs. For fair comparison, all the possible scenarios of predicted parameters are individually computed using strategy-7 i.e. aggregated model with grid constraints but no uncertainty modelling. Therefore, strategy-7 represents the deterministic version of the proposed model which excludes uncertainty modelling.

The aggregated costs are computed using the proposed EMS i.e. including uncertainty modelling, and strategy-7 i.e.

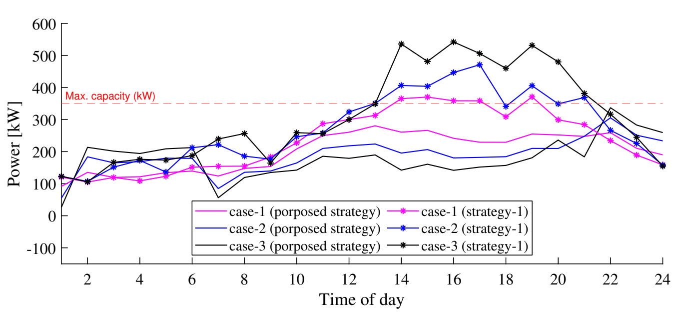

Fig. 7. Load profiles at different EV penetration levels.

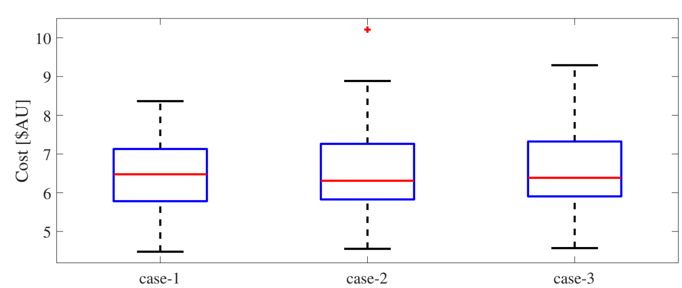

Fig. 8. Cost comparison at different EV penetration levels.

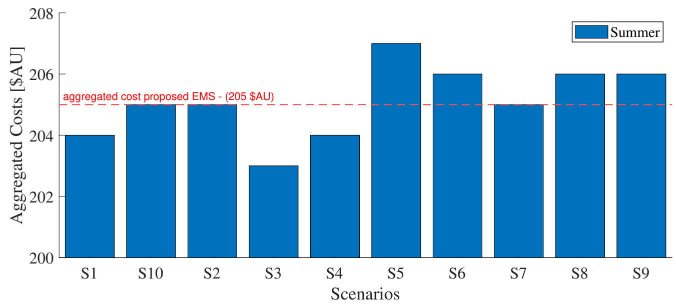

Fig. 9. Aggregated cost for all scenarios during summer comparing the impact of uncertainty modelling between strategy-7 and proposed EMS.

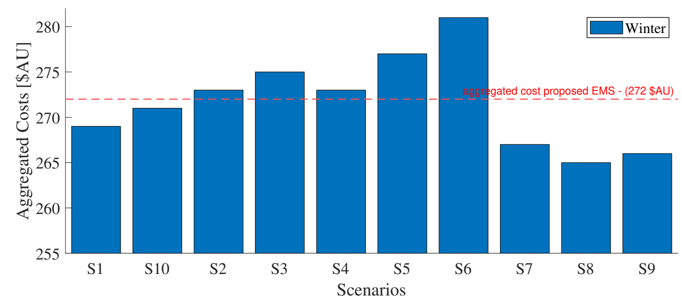

Fig. 10. Aggregated cost for all scenarios during winter comparing the impact of uncertainty modelling between strategy-7 and proposed EMS.

an equivalent strategy excluding uncertainty modelling. The results of 10 randomly selected scenarios are presented in Figs. 9 and 10. It can be noted that the computed aggregated costs for individual scenarios using strategy-7 varies from the aggregated costs computed using the proposed EMS. The aggregated cost computed based on the deterministic model can vary significantly from the actual cost of electricity. However, the proposed EMS evaluates a modest aggregated cost of electricity thus reducing the uncertainty associated with the predicted parameters. It can therefore be concluded that the proposed model can effectively reduce the uncertainties associated with the predicted parameters.

VI. Discussion

An aggregated coordinated framework for charge/discharge scheduling of EVs in an LV residential network is proposed in this paper to minimize the cost of electricity for EV owners and manage the peak demand for grid operators. A comprehensive optimization model for charge/discharge scheduling of EVs is obscure in the existing literature which considers the uncertainties associated with the forecasts, utilizes the batteries on wheels through V2G & V2B flexibilities, accounts for the battery capacity degradation to avoid exploitation of EV batteries, and prioritizes EV owner's preferences.

Simulation results presented in the results section show that the model can reduce the cost of electricity for EV owners significantly while effectively managing the peak load on the grid even with the 100% penetration of EVs as shown in Fig. 7. Detailed analysis show that the adaptability from the EV owners can moderate any grid capacity issues even with full EV penetration. However, the consumer's participation may require attractive incentive plans to guarantee the accessibility of EV flexibilities in such grid support services. The adaptability of the proposed strategy makes it versatile for a large network with a higher penetration level of EVs and other distributed and flexible energy resources. The robustness of the model is validated for different data inputs including the seasonality (summer/winter), day of the week (week-day/weekend), and different levels of EV penetration.

It can be argued that the uncertainty model proposed in this paper does not completely eliminate the risk of uncertainty associated with the predicted parameters. However, it can be noted that the proposed stochastic approach adopted in this study reduces the risk of under or over estimation of the cost of electricity for the aggregator. This approach is better than the deterministic approach as the later can lead to significantly higher variations in the estimated cost of electricity. The future work will focus more on improving the effectiveness of the uncertainty model to minimize the risk of under or estimation for the aggregator while also exploring the large scale applications of EV aggregation with potentially higher impact on the grid.

VII. Conclusion

A comprehensive energy management system for electric vehicle (EV) charge-discharge scheduling is proposed in this paper to minimize the cost of electricity and manage the peak demand in an LV residential network. In contrast to most EV scheduling models, the proposed EMS accounts for uncertainty associated with day-ahead prediction, modelled battery capacity degradation to avoid excessive charging/discharging of EV batteries and ensured that EV owner's preferences are not compromised. EV charge/discharge schedule is optimized using mixed-integer-programming approach and uncertainty of forecasted parameters is compensated using stochastic approach.

The proposed EMS is evaluated via simulation of an LV residential neighborhood in Australia. The simulation results indicate that the proposed framework can effectively prevent grid overloading despite high EV penetration in the network. The proposed strategy can effectively incorporate EV owners' preferences while providing grid-support services. The simulation results prove the efficacy of the proposed strategy by significantly reducing the cost of electricity of the EV owners. Comparison with the state-of-the-art strategies indicate that the proposed strategy can improve the load factor up to 36%, the peak-to-average-ratio up to 27% and cost up to 56% compared to uncoordinated scheduling.

It has been evaluated that EVs can provide significant cost saving opportunities for the EV owners while supporting the grid operators to manage the peak demand, when managed appropriately. Other than residential applications, EVs serving the fleets with predictable schedules can be far more effective in offering grid support services. The future work will be more focused on improving the uncertainty modeling and also analyzing the potential of EVs used in commercial fleets to provide grid support services.

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NOMENCLATURE

Indices and Sets

t	time of day $\in \mathbb{T}$
h	households $\in \mathbb{H}$
d	day of week [week-day,weekend]
s	season [summer,winter]
i	scenario $\in \mathbb{I}$

Parameters

$\mathbb{S}^{d}_{(t,h,i)}$	EV status on day d of house h at time interval t and scenario i
$\mathbb{D}^{d}_{(t,h,i)}$	EV distance travelled on day d of house h at time interval t and scenario i [km]
$\mathbb{A}^{d}_{(t,h,i)}$	EV availability on day d of house h at time interval t and scenario i [0,1]
$\mathbb{E}^{s}_{(h,i)}$	EV efficiency in season s of house h and scenario i [kWh/km]
Ψ^{+}_{t}	Time-of-use tariff
Ψ^{-}_{t}	Feed-in-tariff
ρ_i	Probability of scenario i
$\mathbb{P}^{\mathbb{V}_{chg}}_{\Uparrow}$	Max charging power of EV [kW]
$\mathbb{P}^{\mathbb{V}_{dis}}_{\Downarrow}$	Max discharging power of EV [kW]
$\delta^{\mathbb{V}}_{\Uparrow}$	Max SoC limit of EV [%]
$\delta^{\mathbb{V}}_{\Downarrow}$	Min SoC limit of EV [%]
$\eta^{\mathbb{V}}_{h}$	Charge-Discharge efficiency of EV [%]
θ	Battery degradation cost constant [$/Wh]
γ	Coefficient of battery degradation
$\mathbb{P}^{\mathbb{L}}_{(t,h,i)}$	Household load [kW]
$\mathbb{P}^{\mathbb{K}}_{(t,h,i)}$	Solar generation [kW]
$\overline{\mathbb{P}^{\mathbb{G}}}$	Grid capacity limit [kW]
$\overline{\mathbb{P}^{\mathbb{V}}}$	Aggregated maximum charging power limit for EVs [kW]

Variables

$\alpha_{(t,h,i)}$	Binary auxillary variable [0,1]
$\beta_{(t,h,i)}$	Binary auxillary variable [0,1]
$\mathbb{P}^{\mathbb{V}}_{(t,h,i)}$	EV charge-discharge power [kW]
$\mathbb{P}^{\mathbb{G}}_{(t,h,i)}$	Power demand from grid [kW]
$\delta^{\mathbb{V}}_{(t,h,i)}$	EV state-of-charge [%]
$\Pi_{\mathbb{P}}$	Battery capacity degradation [kWh]
$\mathbb{C}^{\mathbb{V}}_{(t,h,i)}$	EV battery degradation cost [$/kWh]
TC	Total cost of electricity for the aggregator [$]
$HC_{(t,h)}$	Cost of electricity for each household [$]
$EB_{(t,h)}$	Energy bought by each household [$]
$ES_{(t,h)}$	Energy sold by each household [$]
$BD_{(t,h)}$	Cost of battery capacity degaradtion for each EV [$]