A coordinated electric vehicle management system for grid-support services in residential networks

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***Abstract*—Increased integration of light-duty electric vehicle (EV) into the low voltage (LV) residential networks imposes capacity issues for the grid operators. For example, uncoordinated and clustered charging of residential EVs can often overload grid assets, jeopardize network reliability, and can often violate local voltage constraints. This paper proposes a coordinated management system for EVs in an LV residential network with power grid support functionalities to address grid overloading and local voltage constraints violation. The charging and discharging of EV batteries in the network are coordinated via a local EV aggregator. The coordination is realized using multi-agent system architecture that provides the EV owners with full decision-making authority and preserves their privacy. The EV coordination and vehicle to grid (V2G) resource optimization of the EV aggregator is formulated as a mixed-integer programming-based optimization model to minimize the electricity cost for the EV owners based on a real-time tariff while complying with local grid constraints. The proposed methodology is evaluated via ~~simulation~~ on an LV residential network in Sydney, Australia with actual load demand data. The simulation results indicate the efficacy of the proposed strategy for electricity cost reduction of the EV owners while mitigating grid overloading and maintaining desired bus voltages.**

***Index Terms*—Electric Vehicle, Vehicle to Grid, EV aggregator, Multi-agent Systems, Mixed-integer Programing (MIP)**

NOMENCLATURE

Indices and Sets

$t \in \mathcal{T}$	Time periods
$h \in \mathcal{H}$	Residential houses/consumers without EV
$k \in \mathcal{K}$	Residential houses/consumers with EV (the same indices are used to represent EV)
$b \in \mathcal{B}$	Grid bus/point-of-connections of houses

Parameters

Δt	Duration of time period [hour]
P_k^+, P_k^-	Nominal charging and discharging power of EV k [kW]
η_k^+, η_k^-	Charging and discharging efficiencies of EV k
$P_{t,k}^l$	Load demand of EV house k at time t [kW]
θ^{set}	Thermostat set-point temperature
P_{max}	Maximum consumption limit for the neighborhood [kW]
$\overline{V}, \underline{V}$	Maximum and minimum thresholds for bus voltage
r_{bb}, x_{bb}	Resistance and reactance of the line segment connecting bus b with its parent bus

Variables

ρ_t	Real-time tariff at time t [$/kWh]
$s_{t,k}$	State-of-charge of EV k at time t
λ	Internal control signal in per unit for flexibility bids
$d(\lambda)$	flexibility bid as a function of λ
Φ, Ω	State-of-charge flexibility indices of EV
$v_{b,t}$	Voltage at bus b at time t
$\overline{P_t^{agg}}$	Maximum power consumption limit for EV houses within the a cluster [kW]
x	Binary optimization variable

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I. INTRODUCTION

The annual sale of Electric vehicles (EVs) surpassed 2 million in 2018 and increased sales are projected in the coming years due to favorable regulations and technological advancements [1], [2]. The charging demand of this increasing EVs can be met by having additional generation during peak EV demand periods [2] as the total worldwide EV charging demand of 58 TWh in 2018 represents less than 1% of the global electricity demand [1].

The light-duty electric cars represent the major portion of EVs. Most light-duty EVs are usually charged at residential building [1] and can often consume more than the peak demand of the building. Without major grid reinforcements most of the low-voltage (LV) residential distribution networks will not be able to accommodate this increasing EV charging demand due to their limited capacity [3]. Therefore, the localized capacity issues of increased EV integration into the power grids require proper EV management strategies [2], [4].

The utilities around the world introduced dynamic tariffs and various demand response (DR) programs for influencing EV owners to shift their charging to the periods when electricity is cheaper and overall demand on the LV networks is low [5]–[8]. As a result, EV management strategies are increasingly being adopted to gain economic incentives during peak tariff periods that sell energy to the grid using the vehicle to grid (V2G) capability or supply portion of building loads via vehicle to building (V2B) functionalities [9], [10]. However, large-scale adoption of such EV management strategies can create rebound peaks during lower tariff periods [5], [11], [12], and can often introduce clustering problem [6], [13], [14]. The clustering refers to situations when all the EVs in a local area try to charge or discharge at the same time [6], [13], [14], thereby overloading grid assets (e.g. transformer and cables), and in turns degrade their lifetime. Besides, uncoordinated and clustered charging or discharging of EVs can violate local voltage constraints and jeopardize the reliable operation of the network [13]–[15].

Significant research efforts have been made towards developing charge-discharge management strategies of EVs by incorporating localized capacity issues and grid constraints. For example, a web-based day-ahead EV scheduling model is presented in [16] to prevent grid overloading, and [13] proposes a centralized control algorithm to manage EV charging for congestion management and local voltage support for the grid. Authors in [17] proposed a charge-discharge management framework for residential EVs to reduce local voltage-constraint violation induced curtailment of residential PV injection. A modified time of use (ToU) tariff model is presented in [11] to schedule EV charging avoiding grid overloading and local voltage drop. However, the centralized approaches [13], [16] do not cater for convenience and privacy reservation of the EV owners, and the methodology in [17] do not address grid-constraints violations, whereas tariff-based strategy [11] can introduce unfair pricing for some EV owners as their tariffs are affected by the neighbors charging demand. The multi-agent system (MAS) based coordinated strategies have been adopted in several studies to tackle the grid-capacity issues of EV charging as MAS allows conflicting stakeholders to negotiate and optimize their objectives [18], [19]. For example, the authors in [20] and [21] proposed MAS-based EV management systems to prevent distribution grid congestion using price-based scheduling of EV charging demand in the network. MAS-based energy management models of [3], [22] coordinate the flexibilities of controllable building loads and EVs via a local aggregator to reduce the transformer overloading and maintain the desired voltage level at the grid connection points. Coordinated strategies are also used in [4], [23], [24] that manage EV charging to address grid-capacity issues.

However, the methodologies in [20], [21], [23] do not consider the local voltage-constraints violations, which is the major concern of increased EV penetration in the LV networks. On the other hand, the curtailment-based approaches of [3], [22] do not provide the users with full decision-making authority. Moreover, the EV management models in [4], [20], [21] do not incorporate user preferences while determining the flexibility of EVs for grid support services, and the reactive approach of [24] can introduce frequent disruption in EV charging for grid services. In addition to that, the day-ahead scheduling models of [13], [17], [20], [21], [23] are highly dependent on the forecast accuracy as EV availability and myopic human behavior are highly difficult to predict.

To this end, a real-time residential EV management framework is presented that addresses the grid overloading and voltage violations using V2G flexibilities of EVs in the network. The salient features of this paper include:

1) A MAS-based coordinated EV management model is proposed for LV residential networks to prevent overloading and under-voltage situations that may arise due to aggregated and clustered EV charging.
2) Instead of curtailing EV charging for under-voltage nodes (as in [3], [22]), the V2G flexibilities of neighboring EVs are optimally utilized to maintain desired grid voltages. To this end, an improved bidding model is proposed based on the local supply-demand matching methods of [3], [22], [24], [25]. The proposed flexibility bid represents the demand shifting and V2G flexibilities of residential EVs considering EV availability, storage constraints, and user preferences. The active bidding provides the EV owners with full-decision making authority and autonomy, thereby increasing their participation [17].
3) The role of flexibility aggregation is implemented onto a local EV aggregator that interacts with the EV agents and grid agents for grid support services. MAS-based architecture is used to realize the coordination among participating agents. It allows the owners to incorporate their preferences and conveniences for determining charge-discharge flexibilities of EVs, while the network operator and utilities can procure demand-side flexibilities via the aggregator during grid congestions or voltage-constraints violations. The proposed architecture shifts the role of complicated computations to the aggregator and requires limited communication capability, thereby making its practical implementation feasible with market-available and cost-effective embedded devices [22], [26].
4) The coordination problem of EV aggregator is formulated as a Mixed-integer programming (MIP)-based optimization model that minimizes the electricity cost of the EV owner while complying with local grid constraints.

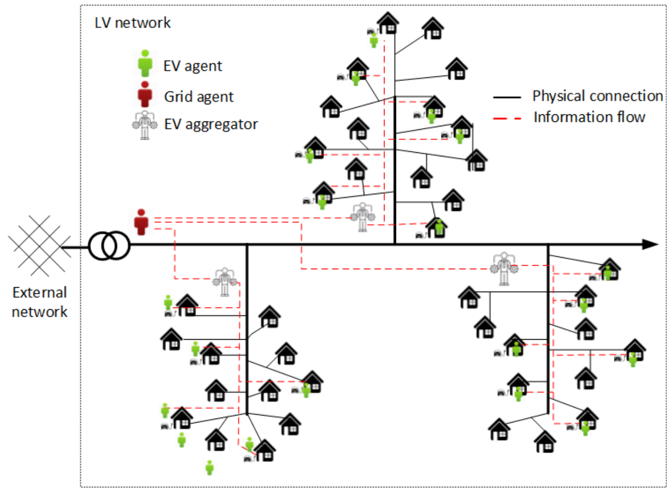

Fig. 1. MAS architecture of the proposed EV management framework

The remainder of the paper is organized as follows, the MAS is presented in Section II, followed by the proposed methodology for EV management in Section III, the simulation studies and results are discussed in Section IV, Section V gives the conclusion of the paper.

II. Description of the MAS architecture

The overview of the MAS architecture for the proposed EV management framework is illustrated in Fig. 1. The framework is developed for an LV residential network, where involved stockholders are represented by software agents. Three types of agents are considered namely grid agent, EV agent and

EV aggregator agent. It is considered that the incumbent communication system is capable of carrying out the necessary information exchanges between the agents for the local coordination.

An EV agent manages the charge-discharge of the connected EV. Based on the users' preferences and operational constraints, the EV agent generates flexibility bids to be sent to the aggregator agent. This allows the users to specify their preferences and preserve their privacy as they do not need to share private information related to EV usage with the aggregator.

An aggregator agent is considered for each congestion points in the network that can represent an LV feeder, a residential neighborhood, or the service area under a distribution transformer. The aggregator agents are responsible for coordinating the EVs within its cluster. Unlike conventional EV aggregator, the aggregator in this paper does not participate in the energy market. Rather it aggregates local EV flexibilities and provides grid services, therefore, the competition among aggregators is considered out of the scope of this paper, and only one aggregator is considered for a cluster of EVs.

The EV agents send flexibility bids to their aggregator agent in each dispatch interval, who determines the equilibrium control signal that complies with the local grid constraints and minimizes the costs for the EV owners. This equilibrium control signal is then broadcast to the EV agents, based on which they dispatch the EVs for charging or discharging.

The grid agent represents the regional distribution system operator (DSO) managing the LV network and responsible for real-time monitoring of the network conditions. Based on the network conditions, the grid agent notifies the EV aggregators within its service area regarding the local grid constraints that include the maximum supply capacity of the congestion points and thresholds for bus voltages.

III. Coordinated EV management system

Figure 2 illustrates the overall system overview of the proposed coordinated EV management model for a cluster of EVs managed by an aggregator. Residential houses without EVs within a cluster are represented by $h \in \mathcal{H}$, whereas the EVs and the houses with EV are indicated by the same indices, $k \in \mathcal{K}$. The proposed EV management system is operated in real-time with discrete time periods of Δt hour, which are represented by $t \in \mathcal{T}$. The buses within the network area of an EV aggregator are indicated by $b \in \mathcal{B}$. It is considered that the EV owners participating in the network support services have a real-time pricing (RTP) tariff contract with the utility as follows:

$$\rho_{t,k} = \alpha_t P_{t,k}^2 + \beta_t P_{t,k} + \gamma_t \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \tag{1}$$

where the dynamic cost-coefficients α, β and γ are considered to be sent to the EV aggregators that can either represent the actual wholesale electricity sport prices or they can be location-specific parameters specified by the electricity suppliers to maintain reliable power supply.

When an EV owner connects the EV to the electrical power outlet, the owner specifies the state of charge (SoC) requirement before the next departure on an EV management interface, in which the functionality of the EV agent is installed. The SoC requirement indicates the target SoC, s^{tar} by a deadline t^{tar}. In addition to that, the EV agent reads the current SoC level, $s_{t,k}$ of the connected EV, and then it is considered to be available for charging or discharging. A dynamic availability matrix, $\mathbf{A}_t$ indicates the available EVs within the cluster, which is updated whenever an owner connects his EV. EV agents determine the flexibility bids of the connected EV whenever it is available and send the bids to the coordinating aggregator. The flexibility bids are sent to the aggregator before every dispatch period and the bids indicate the different levels of power demand or supply of the EV houses for the duration of the next dispatch period with respect to an internal control signal, λ represented in per unit (p.u.). The aggregator agent updates the availability matrix, $\mathbf{A}_t$ whenever an owner connects his EV.

The aggregator coordinates the charge-discharge of the EVs with discrete time steps in real-time (minutes-ahead, as bids are submitted for every dispatch period and before gate-closure of the dispatch periods, which can be 5 - 10 minutes before the actual dispatch period). It requests EV flexibility bids before every dispatch interval represented by t with a duration of Δt. A constant power charge/discharge is considered for a dispatch period of Δt. As the flexibility bids are generated by the EV agents before every dispatch period, the proposed method does not require any uncertainty modeling for EV availability or SoC predictions as in the day-ahead methods of [13], [17], [20], [21], [23]. In addition to that, the proposed bidding reserves the privacy of the EV owners as the current SoC levels, the target SoC, and deadline are not shared with the aggregator, neighbors, and grid agent.

The aggregator also receives the dynamic grid constraints before a dispatch period from the grid agent. The grid constraints indicate the maximum power limit for the cluster to avoid grid overloading and threshold values for the bus voltages within the cluster. Then the aggregator determines the equilibrium control signal, λ^* that corresponds to minimum costs for the EV owners and complies with all the grid constraints sent by the grid agent. It then broadcasts λ^* to the EV agents within its cluster. Upon receiving the λ^*, the EV agent sends the dispatch signal to the connected EV that indicates a charge, discharge or stay idle for that dispatch interval. The process is repeated for every time intervals of $t \in \mathcal{T}$. The following sections discuss the mathematical formulation of the overall methodology in detail.

A. Flexibility bids of EV agents

The EV agent estimates the SoC deficiency and maximum SoC gain before deadline based on the owner-specified SoC requirement, target deadline, and current SoC level. SoC deficiency indicates the SoC shortage from the target SoC if the EV is allowed to discharge at rated power in V2G mode for the current dispatch period. On the other hand, the maximum SoC gain is the maximum additional SoC level the

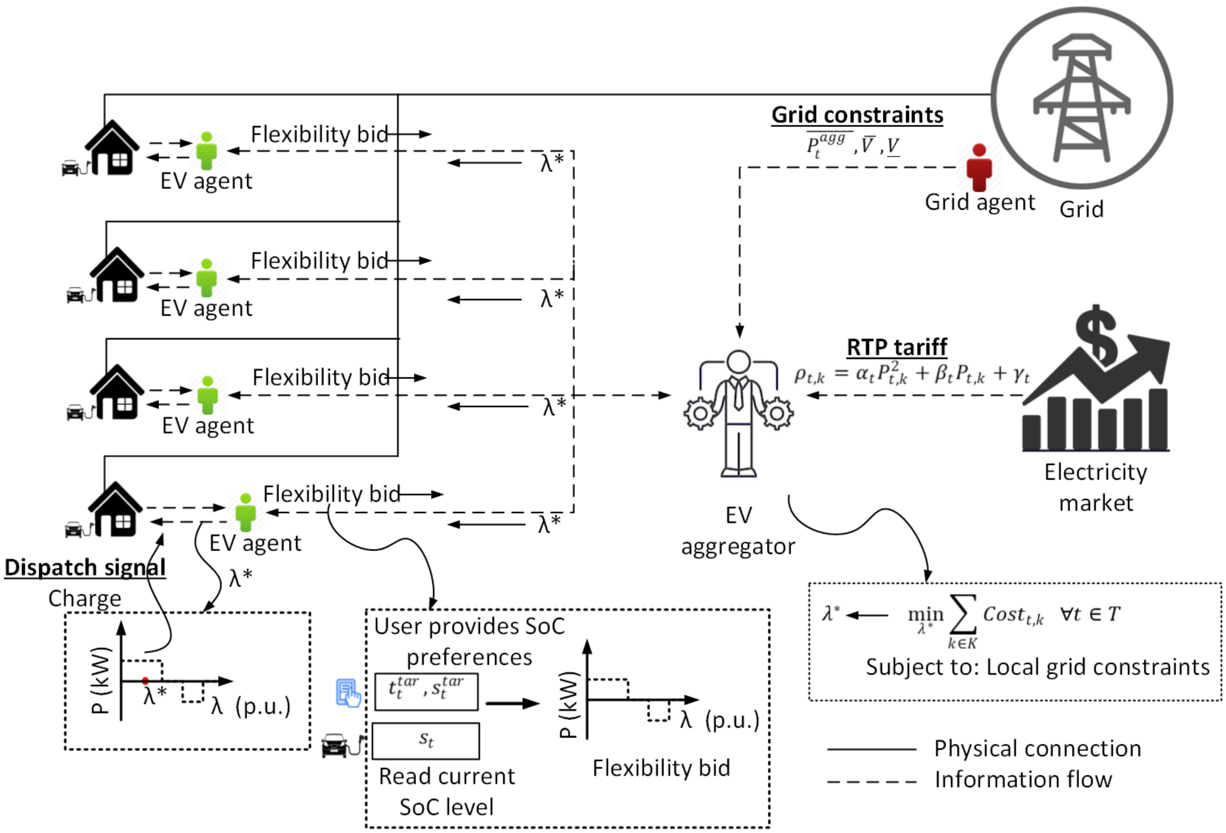

Fig. 2. System overview of the EV management system for a cluster of EVs managed by an EV aggregator

EV can accumulate if it is allowed to charge continuously from current time period, t to the deadline, t_{tar}. Therefore, the SoC deficiency, $s_{t,k}^{def}$ and the maximum SoC gain, $s_{k,t}^{gain}$ can be expressed as:

$$s_{t,k}^{def} = s_{t,k}^{tar} - s_{t,k} - \frac{(P_k^- / \eta_k^-)\Delta t}{E_k^{cap}} \quad \forall t \in \mathcal{T}, k \in \mathbf{A}_t \tag{2}$$

$$s_{t,k}^{gain} = \frac{\eta_k^+ P_k^+ \Delta t (t_k^{tar} - t)}{E_k^{cap}} \quad \forall t \in \mathcal{T}, k \in \mathbf{A}_t \tag{3}$$

where P_k^+ and P_k^- are the nominal rated power for EV charging and discharging respectively, whereas η_k^+ and η_k^- indicate their charging and discharging efficiencies respectively. The maximum rated battery capacity of the EVs are indicated by E_k^{cap}.

When the SoC deficiency is lower than the SoC gain then the flexibility bids of the EV agents are expressed as follows:

$$d_{t,k}(\lambda_{i,t}) = \begin{cases} P_{t,k}^l + P_k^+ & \forall \lambda_{i,t} \leq \Phi_{t,k}, \forall k \in \mathbf{A}_t \\ P_{t,k}^l & \forall \Phi_{t,k} \leq \lambda_{i,t} \leq \Omega_{t,k}, \forall k \in \mathbf{A}_t \\ P_{t,k}^l - P_k^- & \forall \lambda_{i,t} \geq \Omega_{t,k}, \forall k \in \mathbf{A}_t \end{cases} \tag{4}$$

where, $P_{t,k}^l$ represents the load demand, and $d_{t,k}(\lambda_{i,t})$ is the flexibility bid of EV houses, $k \in \mathcal{K}$ during dispatch period, $t \in \mathcal{T}$ expressed as a function of $\lambda_{i,t}$ with $i \in \mathcal{I}$ being the indices of per unit λ values. The flexibility of EV is indicated by two flexibility indices Φ and Ω, which are expressed as:

$$\Phi_{t,k} = \frac{|s_{t,k}^{tar} - s_{t,k}|}{\overline{s_k} - \underline{s_k}} \quad t \in \mathcal{T}, k \in \mathbf{A}_t \tag{5}$$

$$\Omega_{t,k} = \frac{|\overline{s_k} - s_{t,k}|}{\overline{s_k} - \underline{s_k}} \quad t \in \mathcal{T}, k \in \mathbf{A}_t \tag{6}$$

where, $\overline{s_k}$ and $\underline{s_k}$ indicate the maximum and minimum thresholds for the SoC of the EV batteries.

On the other hand, when the SoC deficiency is higher than (or equal to) the SoC gain, then the flexibility bid is expressed as:

$$d_{t,k}(\lambda_{i,t}) = \begin{cases} P_{t,k}^l + P_k^+ & \text{if } s_{t,k}^{def} \geq s_{t,k}^{gain}, \forall k \in \mathbf{A}_t \\ P_{t,k}^l & \text{otherwise} \end{cases} \tag{7}$$

Eq. (7) ensures that the EV does not discharge when there is a big SoC deficiency from the owner-specified target SoC. However, when the SoC deficiency is trimmable by the owner-specified deadline even after discharging the EV for the current dispatch period, then EV agents bids to charge, discharge or stay idle for that period to provide grid-support services. The rationale of the flexibility indices (Φ and Ω) in Eqs. (4) to (6) is that EV agent bids to charge until it achieves target SoC, s^{tar}, beyond that the EV only bids to discharge when it ensures that discharging for one dispatch period would not reduce the SoC below the s^{tar} by the deadline. Otherwise, the EV agents bids to stay idle to retain the SoC level above or the same as the s^{tar}.

B. Grid constraints

In this paper, two types of grid support services are considered- preventing overloading at the congestion points and maintain optimum voltage level in the buses within the cluster. It is considered that, the grid agent monitors the real-time state of the grid conditions, and the load demand of residential houses without EVs, P_h are considered known to the grid agent. Based on this, the grid agent notifies the aggregator regarding the maximum supply capacity, $\overline{P^{agg}}$ for the cluster of EV houses coordinated by each aggregator, which is estimated as follows:

$$\overline{P_t^{agg}} = P_{max} - \sum_{h \in \mathcal{H}} P_{t,h} \quad \forall t \tag{8}$$

where, P_{max} is the maximum power transfer capacity for the congestion point. The grid agent also sends the voltage threshold levels for under-voltage and over-voltage indicated by $\overline{V}$ and $\underline{V}$ respectively. The following power balance constraint is set for the coordination problem of the EV aggregator to prevent overloading:

$$P_t^{agg}(\lambda_{i,t}) = \sum_{k \in \mathcal{K}} P_{t,k}(\lambda_{i,k}) \leq \overline{P_t^{agg}} \quad \forall t, \forall i \tag{9}$$

where $P_t^{agg}(\lambda_{i,t})$ is the aggregated power demand of the coordinated EV houses during t expressed as a function of internal control signal, λ.

On the other hand, to maintain desired voltage levels within the cluster the following constraint is imposed:

$$\underline{V} \leq v_{b,t}(\lambda_{i,t}) \leq \overline{V} \quad \forall b \in \mathcal{B}, \forall t \in \mathcal{T}, \forall i \in \mathcal{I} \tag{10}$$

where $v_{b,t}$ indicates the voltage at bus b within the cluster expressed as a function of λ. The voltages are estimated according to [3], [22] considering a radially operated feeder. For a typical radial feeder, the voltage at bus j at any time can be expressed as:

$$v_{b,t}(\lambda_{i,t}) = v_{b-1,t}(\lambda_{i,t}) - \frac{r_{bb}P_{bb,t}(\lambda_{i,t}) + x_{bb}Q_{bb,t}(\lambda_{i,t})}{v_1} \tag{11}$$

where the impedances of the line segment connecting nodes b and $b-1$ are represented by r_{bb} and x_{bb}, whereas P_{bb} and Q_{bb} indicate the active and reactive power flows of that line segment. It is considered that the grid agent notifies the aggregator regarding the aggregated line flows at each bus for traditional houses within EV.

C. EV Coordination and resource optimization

The aggregator agent coordinates the charge-discharge of the EVs within its cluster based on the flexibility bids of the EVs and optimizes the V2G resources for local grid support service. The EV coordination and resource optimization problem of the EV aggregator is formulated as a mixed-integer optimization problem to minimize the electricity cost for the participating EV houses while complying with local grid constraints. The decision making authority regarding the EV charge-discharge is shifted from the Ev aggregator to the EV agents to reserve EV owners' privacy and autonomy. Therefore, instead of determining the actual charge-discharge schedule of the EVs within the cluster, the EV aggregator determines the equilibrium control signal, λ_t^* for each $t \in \mathcal{T}$ in discrete time steps. As the EV flexibility bids are represented in per-unit values of λ ranging from 0 to 1 with an increment of 0.1, therefore, 11 binary variables are used (represented by $x_{i,t}$ with $i = 1, 2, 3, ...11 \in \mathcal{I}$ for any $t \in \mathcal{T}$), where only one of $x_{i,t}$ can be 1 and corresponding $\lambda_{i,t}$ is identified as λ_t^* . The associated constraints for the binary variables can be written as:

$$\sum_{i \in \mathcal{I}} x_{i,t} = 1 \quad \forall t \in \mathcal{T} \tag{12}$$

According to the RTP tariff, the electricity cost of the EV houses can be expressed as a function of the control signal, λ. Therefore, the objective of the EV coordination and V2G resource optimization of the EV aggregator can be expressed as:

$$\begin{aligned} \min_{\lambda_t^*} \quad & \sum_{k \in \mathcal{K}, i \in \mathcal{I}} \rho_{t,k} d_{t,k}(\lambda_{i,t}) \Delta t \quad \forall t \in \mathcal{T} \\ \text{s.t.} \quad & \lambda_t^* = x_{i,t}\lambda_{i,t} \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{I}, \\ & Eq.\ (1) - Eq.\ (12), \\ & x_i \in [0,1] \end{aligned} \tag{13}$$

D. Dispatching the EVs

Upon receiving the equilibrium control signal, λ_t^* from the aggregator the EV agents determines the dispatch signal for the EVs to either charge or discharge of keep it idle for the current period. So, the actual power consumption of the EVs can be expressed as:

$$P_{t,k}^{ev} = \begin{cases} d_{t,k}(\lambda_t^*) - P_{t,k}^l & \forall t \in \mathcal{T}, k \in \mathbf{A}_t \\ 0 & \forall t \in \mathcal{T}, k \notin \mathbf{A}_t \end{cases} \tag{14}$$

Therefore, the EV k will be charging at t with $P_{t,k}^{ev} = P_k^+$ if $\lambda_t^* \leq \Phi_{t,k}$ and it will discharge with $P_{t,k}^{ev} = P_k^-$ if $\lambda_t^* \geq \Omega_{t,k}$. On the other hand, it will stay idle with $P_{t,k}^{ev} = 0$ if λ_t^* is within $\Phi_{t,k}$ and $\Omega_{t,k}$. The SoC dynamics of the EVs are expressed as:

$$s_{t,k} = s_{t-1,k} + \frac{\eta_{t,k} P_{t,k}^{ev} \Delta t}{E_{t,k}^{cap}} - \sigma_{t,k} \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \tag{15}$$

where $\eta_{t,k} = \eta_{t,k}^+$ while charging and $\eta_{t,k} = \frac{1}{\eta_{t,k}^-}$ when the EV discharges. On the other hand, the SoC usage due to travel is indicated by $\sigma_{t,k}$, and the following SoC constraints is imposed to maintain the SoC level of the EV batteries within threshold levels.

$$\underline{s_k} \leq s_{t,k} \leq \overline{s_k} \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \tag{16}$$

$$s_{t,k} \geq s_{t,k}^{tar} \quad \text{if} \quad t = t^{tar}, \forall k \in \mathcal{K} \tag{17}$$

IV. Numerical validation

This section discusses the simulation studies to validate the efficacy of the proposed method for grid-support services while satisfying user preferences for EV charging.

A. Simulation setup

1) Test network: The proposed EV management framework is evaluated via simulation on an LV residential feeder in Sydney, Australia. The feeder operates radially with a nominal phase-phase voltage of 400V and supplies 42 detached residential buildings. The test network is shown in Fig. 3. The Cable types and line data of the feeder are listed in Table I. It is considered that 15 of the houses in the network are equipped with EVs with V2G capabilities (indicated in red in Fig. 3) and agreed to participate in the grid-support services. An EV aggregator coordinates these 15 EVs in this cluster according to the methodology discussed in Section III-C. The maximum power supply capacity for the feeder is considered as 100 kW, and average voltage thresholds are considered as 1.05 p.u. and 0.95 p.u., which are within the allowed limit according to the standard AS 61000.3.100 [27].

TABLE I
Line data used in simulation.

Cable type	**R(Ω/km)**	**X(Ω/km)**
A: 150 mm^2 Al	0.206	2.5146E-04
B: 95 mm^2 Al	0.320	2.6101E-04
C: 50 mm^2 Cu	0.387	2.2918E-04
D: 35 mm^2 Cu	0.532	2.3555E-04
E: 50 mm^2 Al	0.641	2.7056E-04

2) Load and EV data: The actual meter readings of the 42 houses for a winter weekday are used in the simulation as the load demand data. The EV travel data and availability are taken from the Australian "Smart Grid Smart City" EV trial data [28] for a typical winter weekday. The trial data [28] provides detailed monitoring data for 20 light-duty electric cars including their commute and charging data. Based on [28], the SoC used for EV travel over the simulated day is estimated as described in [24]. The EV battery capacities are considered within 18 - 36 kWh representing typical battery sizes for light-duty electrical cars. The rated powers for charge and discharge are considered as 1.8-3.6 kW for home charging via standard power outlets. The round-trip efficiencies of the EV batteries are considered arbitrarily between 90% - 95%, and the efficiencies for charging and discharging are considered as $\eta_k^+ = \eta_k^- = \sqrt{\eta_k^{rt}}$. The SoC thresholds of all the EV batteries are considered as 10% for minimum SoC and 90% - 100% for maximum SoC levels. The availability of the EVs for dispatch is estimated from the EV trial data [28], where the EVs are considered available whenever they are connected to the home power outlet. The SoC targets of the EVs at departure are estimated from the SoC readings before each trips from the EV trial data [28], which is within 70%-90%. To represent continuity, the final SoC requirement at the end of the day ($t = 96$) is considered the same as the initial SoC at the beginning of the day.

3) RTP tariff: The RTP tariff model proposed for the Australian residential consumers in [7] is used in this paper. The corresponding dynamic tariff coefficients are listed in Table II along with the peak, off-peak and shoulder tariff periods.

TABLE II
Dynamic RTP coefficients

Tariff periods	α_t	β_t	γ_t
Peak (2PM - 8PM)	0.036	0.1413	0.4
Off-peak (10PM - 7AM)	0.013	0.0024	0.15
Shoulder (7AM - 2PM, 8PM- 10PM)	0.019	0.0242	0.35

4) Simulation environment: The simulation is run for a typical winter weekday and a 15 minute EV dispatch interval is considered. Load demand and EV charge-discharge power are considered constant for each simulation period of 15 minutes, therefore average power is considered. Besides, the average voltage is estimated according to Eq. (11), and it is considered that the incumbent EV charge controller can use this as a reference for appropriate control strategy, which is considered out of the scope of this paper. The MAS architecture is developed in Java Agent Development Environment (JADE), the EV flexibilities are modeled in Matlab and the optimization model is formulated in General Algebraic Modeling System (GAMS) and solved using Baron solver with an absolute and related optimality gap of 0. None of the problems took more than 1 second on an Intel Core i7 3.40 GHz computer with 16 GB of RAM. The communications between Matlab and JADE are established using TCP/IP, and GAMS Data Exchange (GDX) is used to interface between Matlab and GAMS.

5) EV scheduling strategies: Based on the input data discussed in the preceding sections, numerical simulation tests are conducted for the proposed coordinated EV management methodology. In addition to that, to compare the efficacy of the proposed method, the results are compared with the following EV management strategies:

- Strategy 1-Inflexible scheduling: In this case, the EV charging data from the EV trial data [28] for the simulated day is considered. This strategy represents an inflexible charging of the EVs as the V2G and V2B functionalities of the EVs are not considered in this strategy, therefore it represents a worst case scenario. The electricity cost of the houses with EVs are compared both for time-of-use (ToU) tariff and RTP tariff. The incumbent ToU tariff rates of the regional electricity retailer are considered with peak, off-peak and shoulder rates as 53.01, 14.42 and 23.79 ¢/kWh respectively.
- Strategy 2-Decentralized scheduling: In this case, it is considered that the EVs are individually scheduled in day-ahead according to the methodology presented in [12] i.e the optimization problems for the individual EVs are formulated as a mixed-integer problem as:

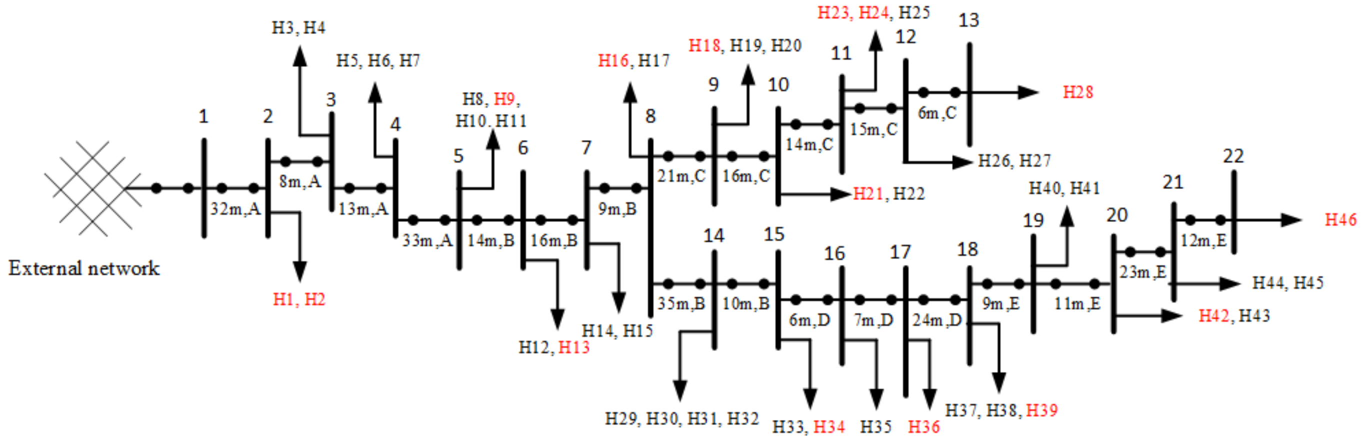

Fig. 3. Test feeder used for simulation.

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\begin{aligned}
\min_{P^{ev}_{t,k}} \quad & \sum_{t\in\mathcal{T}} \rho_t(P^l_{t,k} + P^{ev}_{t,k}\Delta t) \quad \forall k \in \mathcal{K} \\
\text{s.t.} \quad & P^{ev}_{t,k} = x^+_{t,k}P^+_{t,k} - x^-_{t,k}P^-_{t,k} \quad \forall t, k, \\
& x^+_{t,k} + x^-_{t,k} \leq 1 \quad \forall t \in \mathcal{T}, \\
& Eq.\ (15) - Eq.\ (17), \\
& x^+_{t,k} \in [0,1], x^-_{t,k} \in [0,1]
\end{aligned}
\tag{18}
$$

where the binary variables $x^+_{t,k}$ and $x^-_{t,k}$ determines the charging and discharging schedules of the EVs. As, the EV owners do not have any special contracts with utility for grid-support services, therefore, existing retail tariff structure of the region is considered in this case. As a result, the EV houses only sell energy to the grid when it is economically feasible for them. Two tariff scenarios are considered for this scheduling strategy. In the first scenario, the incumbent ToU tariff are considered for demand and feed-in-tariff (FiT) is considered for supply. It is to be noted that, the scheduling strategy limits power injection into the grid for this tariff scenario due to significantly lower FiT of the region [7], [12]. So, the EVs mostly utilize their V2B mode to reduce electricity cost. However, the tariff for demand and supply are considered the same for the second tariff scenario of this scheduling strategy, and the dynamic RTP tariff discussed in Section IV-A3 are used for both demand and supply. Therefore, it utilizes the full flexibility of EV for cost minimization of the user.

B. Results and discussion

Based on the input data, the simulation is run for 24 hours in discrete periods of every 15 minutes. During each period, the EV agents generate and submit flexibility bids to the aggregator if the EVs are connected to the power outlet. The aggregator agent also receives the grid constraints and RTP from the respective agents. Then, it runs the optimization model of Eq. (13) and determines the equilibrium control signal, λ^*, which is then sent to EV agents. Based on this the EV agents dispatch the EVs either to charge or discharge or to stay idle for this dispatch period of 15 minutes. The same process is repeated in every dispatch periods until the end of the day. The equilibrium control signals throughout the day are shown in Fig. 4. According to the proposed methodology, the higher values of λ^* would encourage more EVs to discharge in V2G, whereas the lower λ^* means more EVs would tend towards charging. However, in all cases, the EVs will charge or discharge when it does not violate any user preferences. To maintain continuity, the SoC level at the end of the day is considered the same as the SoC at first period of the day.

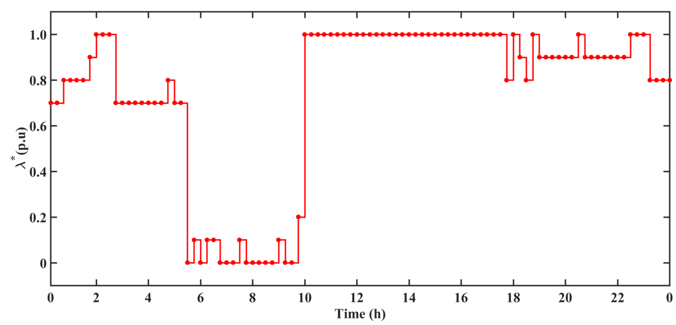
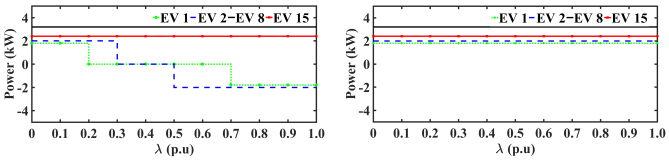


Fig. 4. Equilibrium control signal

C. EV owners' preference reservation

To illustrate the preferences reservation of the EV owners, the flexibility bids of selected EVs (no. 1, 2, 8 and 15) are shown in Fig. 5 for two periods (2 AM and 6 AM). The corresponding SoC levels of these EVs at these times are listed in Table III along with the SoC targets of the EV owners. It can be noticed that both EV 1 and 2 have sufficient SoC at 2 AM compared to the SoC targets, therefore they are flexible enough to either charge or discharge to provide grid support services. As a result, the flexibility bids of these EVs in Fig. 5a show that they would discharge for higher values of λ compared to their flexibility indices as discussed in Section III-A. However, the SoC deficiency of EV 8 and 15 at 2 AM is high compared to their SoC targets before departing in the morning. Therefore, they only bid to charge as can be seen in Fig. 5a. On the other, all the EVs bid to



(a) 2 AM ($t = 8$)   (b) 6 AM ($t = 24$)

Fig. 5. Flexibility bids of selected EVs at 2 AM and 6 AM

TABLE III
SoC LEVELS OF SELECTED EVs AT 2AM AND 6AM

EV # (k)	t_k^{tar}	s_k^{tar}	$s_{t,k}$	
			2AM ($t = 8$)	6AM ($t = 24$)
1	31	78 %	78 %	78 %
2	26	72 %	72 %	72 %
8	25	85 %	75 %	85 %
15	30	95 %	79 %	94 %

charge irrespective of the value of λ at 6 AM as the departing times are approaching and they need to achieve (or retain) a particular SoC level (equal or higher than the owner-specified target level). The proposed method ensures that the EVs are charged according to the owners' SoC targets even if they want a full-charged EV (the case for EV 15, 95% is its maximum SoC). In addition to that, the owners can also decide not to participate in any grid support services by simply plugging out the EVs whenever they are fully charged (or charged up to their desired level). Therefore, it can be argued that the proposed method reserves EV owners' preferences all the time and it provides them with the full-decision making authority. Moreover, the proposed method also reserve their privacy as they do not need to share their private information such as current SoC or target SoC of the EVs. Besides, it also ensures their autonomy as their EVs are not remotely controlled by any external entities, unlike direct-control based methods.

D. Effect of EV scheduling on Grid overloading

The aggregated load demand of the cluster is depicted in Fig. 6, where the effectiveness of the proposed method is compared with the other EV scheduling strategies for grid overloading mitigation. It can be seen that the aggregated demand of the cluster stays below the maximum supply capacity of the grid throughout the day when the EV charging demands are excluded (as indicated by w/o EV in Fig. 6). As the simulation was conducted for a winter day, comparatively higher demand is seen during the evening, night, and early morning due to higher electric heater demand. In the case of scheduling strategy 1 for EV charging, the aggregated demand exceeds the maximum capacity in the evening as almost all the EVs arrive at home and start charging during evening 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

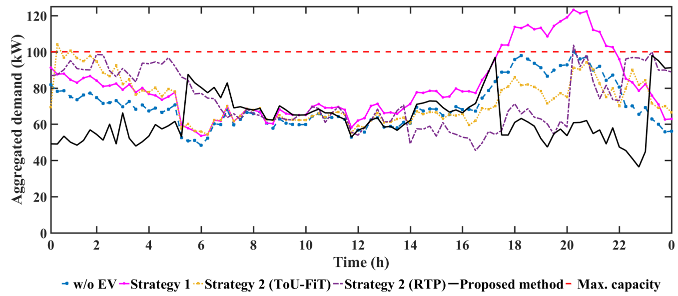


Fig. 6. Aggregated demand of the network

the EVs thereby reducing the overall demand on the grid, especially during peak tariff periods. There are a few ramp-ups and ramp-downs incidents noticed in the aggregated demand for the proposed method especially during the tariff transaction periods. The main reason behind this is that the EV flex bids avoid charging during peak tariff periods and some EVs even bid to discharge during these periods to get financial profits. The aggregated demand for strategy 2 stays below the maximum capacity for both tariff scenarios except for 1-2 instances. This strategy minimizes the energy consumption of the houses during peak demand periods due to higher tariffs. Therefore, a higher aggregated demand is seen during off-peak tariff periods for the ToU-FiT tariff case. On the other hand, the aggregated demand also exceeds the maximum capacity for the RTP tariff case in the evening to maintain the required SoC level at the end of the day. However, the total daily energy demand of this strategy for the ToU tariff case is much higher than the proposed method as V2G flexibilities of the EVs are not effectively utilized due to lower feed-in-tariff of the region. On the other hand, the proposed methodology utilizes V2G during voltage-constraints violation or when aggregated power demand exceeds maximum supply capacity thereby reduces the overall energy demand of the cluster over the simulation window.

E. Effect of EV scheduling on the average voltage profiles

The major concern of the higher EV penetration along a feeder is the local voltage-constraint violation and the further away from the distribution transformer the point of connection (POC) is the higher is the impact on voltage level [22]. For this reason, to accommodate the voltage drop along the feeder, a comparatively higher voltage is set at the residential distribution transformer [3], [22]. For the simulation, it is considered that the voltage at bus 1 of the test network is set at 1.02 p.u. to manage under-voltages along the feeder. The voltage at the other 21 buses of the test network is shown in Fig. 7. As the voltage drops are much severe at the furthest bus, the voltage profiles of the bus 22 are also illustrated in Fig. 8 for all EV scheduling cases.

It can be seen in Fig. 8 that, the voltage stays above the lower threshold of 0.95 p.u. when EV charging are excluded (w/o EV case in the figure). However, with the introduction of EVs the voltage falls below the minimum threshold in case of scheduling strategy 1 causing under-voltage (as shown in

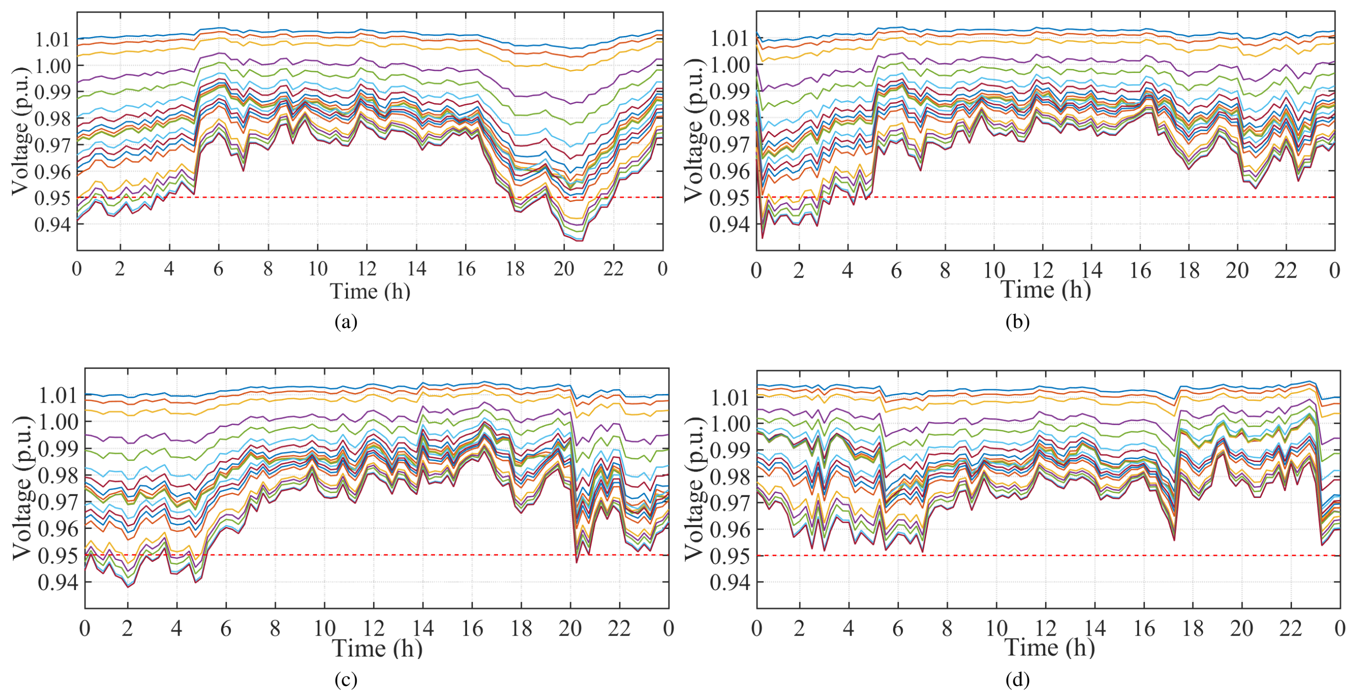


Fig. 7. Bus voltage. (a) Strategy 1 (b) Strategy 2 (c) Strategy 3 (d) Proposed method

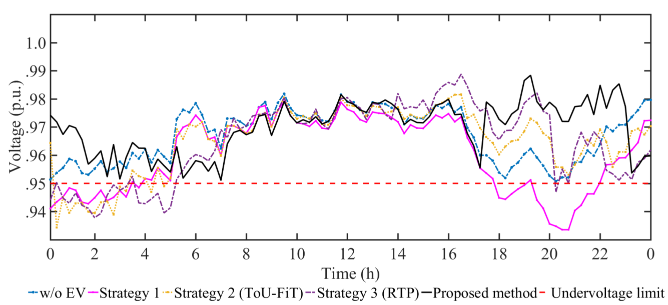


Fig. 8. Voltage at furthest bus ($b = 22$)

Fig. 7a and Fig. 8). However, the scheduling strategy 2 shifts most of the EV charging from peak evening periods to off-peak periods (10 PM - 7 AM). As a result, Figs. 7b and 7c and Fig. 8 show that under-voltages during the evening hours are mostly prevented for strategy 2, however, sustained under-voltages are noticed during off-peak hours especially between 12 AM and 5 AM as most EVs are charging during this time to reduce charging cost. On the other hand, the proposed coordinated strategy prevents any under-voltage instances throughout the day as seen in Fig. 7d and Fig. 8.

F. Efect of EV scheduling on the electricity cost savings

The electricity costs of the houses with EVs are listed in Table IV for the simulated day. It can be seen that the optimized scheduling strategy 2 can significantly reduce the electricity cost for both the ToU and RTP tariff compared to strategy 1. Because such optimized methods shift the EV charging from peak tariff periods to off-peak hours. The proposed coordinated method also offers significant cost savings compared to strategy 1 for almost all the EV houses. However, for some EV houses, the individual optimized EV scheduling (strategy 2) performs better than the proposed method in terms of electricity cost savings (as can be seen from houses # 1, 13, 16, 21, 23, 36, 42 and 46). This is because, the proposed method minimizes the electricity cost while complying with local grid-constraints, which prevents some of the EVs to be charged during off-peak periods as it might lead to overloading or under-voltage situations. Even though specific RTP model for Australia is used in the simulation studies, similar results are expected for different RTP or other pricing schemes widely used in electricity markets around the world, such as time-of-use (ToU) pricing or a combination of ToU with feed-in-tariff (FiT).

Therefore, EV owners need to be offered attractive incentives that encourage them to participate in such grid-support services irrespective of the pricing scheme. However, from the grid operators' perspective it would be economically feasible to offer the EV owners the expected cost savings they would achieve by adopting individual optimal EV charging. Because the alternative and traditional solution to address the grid capacity issues (especially for LV networks) is to invest in grid reinforcement. An economic comparative analysis in [12] shows that incentivizing the EV owners' for their flexibility would be a much more economical option rather than investing in grid-reinforcements. Besides, grid-constraints violation can lead to consumers' load (or supply) curtailment under most of the existing market constructs, thereby affecting consumers' profitability and conveniences [3], [17], [22], [24]. Therefore, utilizing demand-side flexibility for addressing local grid-capacity issues is beneficial for both the consumers and the grid.

TABLE IV
ELECTRICITY COST FOR THE HOUSES WITH EVs

Scheduling Strategy	Tariff	Electricity cost for the simulated day ($ AUD)														
		H #1	H #2	H #9	H #13	H #16	H #18	H #21	H #23	H #24	H #28	H #34	H #36	H #39	H #42	H #46
Strategy 1	ToU	16.57	10.37	15.26	23.07	19.96	12.27	17.77	26.28	17.22	14.70	18.73	22.38	19.17	14.95	23.52
Strategy 1	RTP	20.55	12.14	17.97	39.34	30.75	14.24	28.02	47.32	33.16	22.47	24.63	43.17	27.13	22.67	39.33
Strategy 2	ToU	8.00	6.10	10.53	13.56	9.66	9.67	13.27	20.12	9.79	8.99	11.59	12.20	14.65	11.11	20.64
Strategy 2	RTP	6.99	4.32	8.66	12.60	8.00	8.82	13.89	36.05	9.78	7.11	11.84	13.67	17.13	15.45	24.22
Proposed method	RTP	9.05	2.80	8.00	17.94	15.94	5.95	15.06	34.02	6.68	6.78	11.35	20.58	14.21	16.51	27.45

G. Effect of EV penetration on the performance

The penetration levels of EVs and their corresponding locations within the network can significantly affect the grid loading conditions and voltage profiles. This, in turn, can have an impact on the performance of the proposed management methodology for grid support services. For this reason, 3 case studies are conducted to evaluate the performance with different penetration levels of EVs in the network. Case 1 considers one-third (15 out of 46) of the houses within the network are equipped with EVs, which is the same as the studies discussed in previous sections. A two-third (30 out of 46) EV penetration is considered in case 2, whereas all houses are equipped with EVs in case 3. The locations of the EVs are arbitrarily selected in cases 1 and 2. The availability, battery capacities, charge-discharge efficiencies, SoC requirements, and battery usage for daily commute are selected according to Section IV-A2. In addition to that, the SoC constraints for the end of the day (i.e. $t = 96$) is specifically set to the initial SoC at the beginning of the day to maintain continuity.

Simulation results indicate that available V2G flexibilities are not sufficient at times to mitigate grid overloading and undervoltage situations without increasing grid capacity or violating EV owners' requirements. To investigate the potential impacts for full EV penetration (as in case 3), two scenarios are compared in case 3. The first one focuses on capturing the maximum flexibility potentials of the EV owners. Therefore, the SoC requirements for the final period ($t = 96$) are specifically set to the minimum SoC level in this scenario. On the other hand, the second scenario of case 3 maintains the user-specific SoC requirements similar to the other cases, however, relaxes the grid constraints when V2G flexibilities are not enough to prevent grid constraints violation without affecting owners' requirements. For this reason, the thresholds for grid loading and voltage levels are relaxed in an iterative manner until grid-constraints are satisfied without affecting owners' requirements. Results for the second scenario of case 3 indicate that Eq. (13) has an optimal solution for $P_{max} = 130$ and $\underline{V} = 0.9$.

The aggregated load profiles for the network in all cases are shown in Figure 9. It can be seen that the proposed method can mitigate grid overloading without any capacity expansion up to 66% of EV penetration (case 1 and 2), even though there were significant grid overloading instances noticed if EV owners adopt inflexible (strategy 1) or individually optimized (strategy) approaches to charge their EVs. However, the maximum power transfer capacity of the network has to be increased to 130 kW to accommodate EV charging when all

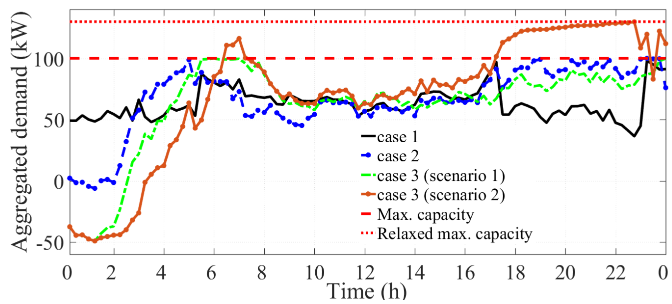


Fig. 9. Aggregated load profile in different cases

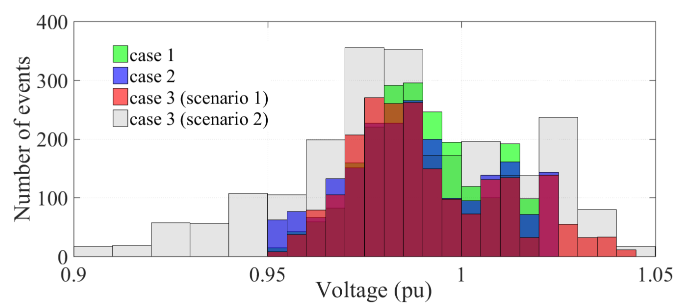


Fig. 10. Histogram of bus voltages in different cases

houses in the network are equipped with an EV. Nonetheless, when the SoC requirement constraints at the end of the day are removed (the first scenario of case 3), the existing grid capacity of 100 kW is found to be sufficient to accommodate full EV penetration. This is because, without these SoC requirements, EVs can discharge to the minimum allowed SoC level (which is considered as 10%), thereby reducing the peak grid demand in the evening periods.

The histogram of the bus voltages for each case is shown in Figure 10. It can be seen that the proposed method can maintain the desired voltage level by utilizing V2G flexibilities of the EVs in the network for the first two cases. The undervoltage situations with full EV penetration can be completely mitigated only if final SoC requirements are removed as indicated by the first scenario of the case 3. However, as discussed before, a minimum voltage level of 0.95 p.u. can not be maintained with a full EV penetration without considering maximum user flexibility (2nd scenario of case 3).

The distributions of the EV owners' daily electricity costs for all cases are illustrated by the box plots in Figure 11. With higher EV penetration, the power drawn from the grid can be minimized in peak periods by using V2G flexibilities.

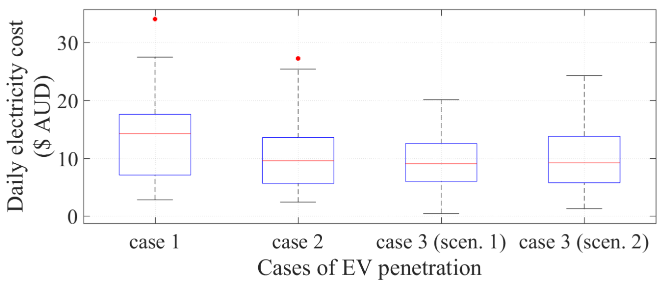


Fig. 11. Distribution of EV owners' daily electricity cost for different EV penetration levels

Therefore, Figure 11 shows that their electricity cost is reduced with higher EV penetration. However, the median, minimum, and maximum cost of the EV owners are higher in the second scenario of the case 3 than that of the first scenario. This is because EVs discharge more in the evening peak periods in the first scenario due to exclusion of SoC requirements for $t = 96$. As a result, peak demand is lower, which in turn, reduces the electricity cost. In addition to that, some EV houses even discharge more than the load demand of the house, thereby offering profit for the owner and further reduces the net electricity cost. On the other hand, the second scenario of case 2 has a higher grid supply capacity (130 kW instead of 100kW of other cases) and includes final SoC requirements for $t = 96$. As a result, EVs have to charge in the evening periods to charge up to user-specific SoC requirements at the end of the day ($t = 96$). Therefore, electricity cost becomes higher compared to the first scenario.

This is to be noted that, the final SoC requirements do not necessarily affect the EV usage or daily commute of the owners as EVs can accumulate the depleted batteries after midnight until the departure the next morning. However, if severe grid overloading or undervoltages are frequent and occur daily, then the EVs might need to discharge to the lowest SoC by every midnight, which can affect owners' conveniences. Besides, it can also lead to the degradation of the EV batteries due to irregular SoC profiles [12]. Therefore, appropriate financial incentive packages are required to encourage EV owners' participation in the grid support functions. Besides, attractive incentives are also essential to ensure sufficient participation from the EV owners with adequate flexibility to address critical grid issues [17].

V. Conclusion

A coordinated EV management framework has been proposed in this paper for residential LV networks to provide power grid support for preventing grid overloading and undervoltages. The charge-discharge of EVs are coordinated and optimized via a local EV aggregator to minimize the electricity cost of the EV owners while complying with local grid constraints. Contrary to most EV management model, the proposed framework shifts the decision making authorities to the EV owner by using MAS-based architecture as it allows individual agents to satisfy their objectives. In addition to that, it reserves the EV owners' privacy, preferences, and autonomy while shifting complex computations to the aggregator, thereby facilitating feasible implementation. The scalability of the proposed framework makes it adaptable for a larger network with a higher penetration level of EVs and other distributed and flexible energy resources.

The efficacy of the proposed methodology is evaluated via several case studies on a test network for an LV residential feeder in Sydney, Australia. The simulation results indicate that the proposed framework can effectively prevent all grid overloading and under-voltage situations. Simulation results also illustrate that instead of curtailing charging demand of EVs responsible for grid constraints violations, the flexibilities of neighborhood EVs are utilized to address these issues. As a result, the proposed method can effectively incorporate EV owners' preferences while providing grid-support services. Detailed analyses with various EV penetration level indicate that grid-capacity expansion is essential to accommodate a 100% EV penetration. However, case studies also indicate that the maximum flexibility from the EV owners can mitigate any grid-capacity issues even with full EV penetration.

However, user autonomy might necessitate attractive incentive schemes to ensure the availability of EV flexibility in such grid-support services as results indicate unfavorable cost reductions for some EV owners. Future research of the authors will be focused on developing proper incentive structure for EV flexibilities in grid support services, which was not considered in this paper. In addition to that, the competition among EV aggregators and their strategic interactions will also be explored in future researches.

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