

Received March 7, 2021, accepted March 18, 2021, date of publication March 22, 2021, date of current version March 30, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3067950

Energy Management Systems for Residential Buildings With Electric Vehicles and Distributed Energy Resources

SOHAIB RAFIQUE¹, (Student Member, IEEE),
MOHAMMAD JAHANGIR HOSSAIN², (Senior Member, IEEE),
MOHAMMAD SOHRAB HASAN NIZAMI¹, (Member, IEEE),
USAMA BIN IRSHAD¹, (Student Member, IEEE),
AND SUBHAS CHANDRA MUKHOPADHYAY¹, (Fellow, IEEE)

¹School of Engineering, Macquarie University, Sydney, NSW 2109, Australia

²School of Electrical and Data Engineering, University of Technology Sydney, Sydney, NSW 2007, Australia

Corresponding author: Sohaib Rafique (sohaib.rafique@hdr.mq.edu.au)

ABSTRACT This paper proposes two electric energy management systems (EMSs) in the context of a grid-connected residential neighbourhood with electric vehicles (EVs), battery storage, and solar photovoltaic (PV) generation. The EMSs were developed to minimize the cost of electricity whilst having no impact on routine individual energy needs and travel patterns. The EMSs were evaluated using common sets of real data with the aim to compare the effectiveness of a centralized EMS with decentralized EMS. The models also accounted for the battery capacity degradation and the associated costs. Simulation studies and numerical analyses were presented to validate the effectiveness of the proposed EMSs considering a high-density residential building in Sydney, Australia. The simulation results indicate that the centralized EMS is more effective compared to the decentralized EMS in terms of cost savings. It is also observed that the energy management strategies significantly reduce the energy drawn from the grid compared to un-optimized energy management schemes.

INDEX TERMS Energy management systems, electric vehicles, optimization, centralized, decentralized, apartment building.

Nomenclature

Indices and Sets

$t \in T$ time interval
 $h \in H$ households

Parameters

\mathbb{A} availability matrix
 \mathbb{D} distance matrix [km]
 \mathbb{S} status matrix
 \mathbb{E} energy efficiency [kWh/km]
 \mathbb{X} set of scenarios for solar PV generation and fixed load (household/bus depot)
 \mathbb{J} set of scenarios for distance travelled by electric vehicles and energy efficiency

The associate editor coordinating the review of this manuscript and approving it for publication was Moayad Alokaily¹.

\mathbb{Z} set of forecast for solar PV generation and fixed load (household/bus depot)
 π^+ day-ahead energy tariff - buy
 π^- day-ahead energy tariff - sell
 $\bar{\chi}^V$ maximum capacity of EV battery
 $\bar{\chi}^B$ maximum capacity of stationary battery
 $\underline{\delta}_V$ maximum SOC limit of EV battery
 $\underline{\delta}_B$ minimum SOC limit of EV battery
 $\underline{\delta}_B$ maximum SOC limit of stationary battery
 $\underline{\delta}_B$ minimum SOC limit of stationary battery
 λ SOC required for distance travel needs
 Ω cumulative SOC required for distance travel needs
 η_c^B charging efficiency of stationary battery
 η_d^B discharging efficiency of stationary battery
 η_c^V charging efficiency of EV
 η_d^V discharging efficiency of EV
 θ^V unit cost of EV battery capacity degradation [\$/kWh]

θ^B	unit cost of stationary battery capacity degradation [\$/kWh]
$\overline{P}(V)$	maximum charging-discharging power limit for EVs [kW]
$\overline{P}(B)$	maximum charging-discharging power limit for stationary battery [kW]
\overline{P}	maximum grid capacity limit [kW]

Variables

δ_t^V	EV battery SOC [%]
δ_t^B	Stationary battery SOC [%]
Π^V	EV battery capacity degradation [kWh]
Π^B	stationary battery capacity degradation [kWh]
∂^V	cost of EV battery capacity degradation [\$]
∂^B	cost of stationary battery capacity degradation [\$]
\mathcal{P}	power flow from/to grid [kW]
\mathcal{K}	solar PV generation [kW]
\mathcal{L}	household/fixed depot load [kW]
α	binary auxiliary variable for day-ahead energy market
β	binary auxiliary variable for day-ahead energy market
\mathcal{V}_t^c	charging power for EV [kW]
\mathcal{V}_t^d	discharging power for EV [kW]
\mathcal{B}_t^c	charging power for stationary [kW]
\mathcal{B}_t^d	discharging power for stationary battery [kW]

I. INTRODUCTION

The residential sector accounts for 27% of the global energy consumption of which buildings alone are responsible for three-quarters of total residential energy consumption [1]. Adoption of renewable energy resources is a globally accepted solution to this problem. However, the installation of renewable energy resources in high-density apartment buildings is usually a challenge due to constraints on the available space.

While the transport sector accounts for about 40% of global fuel consumption [2] but is expected to become increasingly electrified in coming years [3], which may in turn have a significant impact on the electricity grid if not well managed. Additional challenges arise when the EVs are located in the high-density residential buildings. High-density residential buildings present some significant challenges for i) integration of renewable energy generation (due to limited space), and ii) transport electrification (due to limited electrical supply and potential grid impacts of EV charging). Nevertheless, it has recently been shown that the potential negative impacts of EV charging in residential neighbourhood can be significantly reduced using charge management strategies considering local generation and transport needs [4].

A. LITERATURE REVIEW

Many studies have been reported on EMSs designed for grid-connected domestic consumers, with various

combinations of renewable generation, EVs, stationary battery storage, etc. Few studies have specifically considered high density residential buildings. An increasing number of reports concern EMS for individual households incorporating EVs. These reports are often differentiated by their particular emphasis, e.g., on maximizing the synergies between PV generation and EVs in minimizing the potential negative grid impacts of EVs [5]–[11], and/or on minimizing total energy costs [7]–[11] etc. Authors in [12]–[14] presented methods to minimize the cost of electricity for buildings integrated with stationary battery storage and solar PV generation. However, these studies did not account for charging and discharging of EVs while also ignoring the limitations of distributed generation capacity installation in high density residential buildings.

Some of the latter works include extensions to an aggregated EMS, e.g., for a neighbourhood [15], whilst others focus solely on the design and performance of aggregated EMSs for an office building [16], [17] or apartment block [4]. These EMS are also usually optimized with respect to a specific metric of interest, e.g., to minimize aggregated grid impacts and/or energy costs [10], but few consider the scenario-based travel and charging patterns. The authors in [18] developed the optimal framework for aggregated participation of smart buildings integrated with energy storage units, solar PV and EVs, in the day-ahead energy and reserve markets. Notably, most of the studies (except for [4], [16], [18], [19]) allowed for bidirectional charging of the EVs, i.e., vehicle-to-grid (V2G) and/or vehicle-to-building (V2B) capabilities.

Authors in [4] investigated the charging strategies of multiple plug-in hybrid EVs in high density residential building integrated with solar PV generation. Authors in [20] presented a model for charge-discharge scheduling of EVs to minimize cost. Energy management systems were presented by authors in [21], [22] for the high-density residential building with vehicle-to-home (V2H) flexibilities. A home energy management system was presented by authors in [23], using the battery of an EVs. None of the studies discussed above included stationary battery storage flexibilities.

The authors in [24] presented vehicle-to-grid (V2G) coordination schemes for office buildings equipped with EV charging stations. The authors in [25] analysed the impact of solar PV systems on stationary battery storage and EVs in micro-grids. The authors in [7] proposed the EV and stationary battery scheduling for a number of interconnected grids and proposed optimal commitment of the resources. However, these studies were based on non-residential buildings where the vehicle availability patterns are more predictable compared to residential buildings.

An aggregated energy management service was proposed by authors in [19] for energy consumers and distributed energy resource owners in high density residential buildings. The service consists of a business model for billing and distribution of the benefits of aggregation, and a model predictive control algorithm for managing and optimizing energy

resource operations. The aggregator service is expected to reduce the pay-back period of the investment. However, the model did not include variable demand related to travel patterns of the EVs.

Of the referenced works, only [17] provides a direct comparison between centralized and decentralized bi-directional EV charger control systems. The latter study was in the context of a smart office building in which the EMS is optimized to minimize the peak-to-average-power-ratio (PAPR). It was shown that centralized management also reduced total energy consumption and costs, however the system did not consider battery degradation and did not include PV generation or stationary battery storage.

B. CONTRIBUTIONS

This paper addresses the challenges in energy management that arise in high density residential apartment buildings with a limited supply of intermittent renewable generation, together with stationary battery storage and a high concentration of vehicle-to-grid (V2G) capable EVs [26]. This paper presents two energy management strategies, namely a customer-based-strategy (CBS) [26] and an aggregator-based-strategy (ABS) [27], with the aim to minimize the cost of energy consumption for each consumer without compromising their comfort or travel requirements. The research investigates, demonstrates, and compares the cost reduction and other benefits of two distinct EMSs. Constrained optimization of each EMS i.e., CBS and ABS, was undertaken considering energy tariffs, travel needs, and battery degradation. The optimized strategies were evaluated and compared with respect to their cost. The key contributions of this paper are to:

- 1) design a centralized EMS i.e. ABS, for coordinated management of EVs to minimize cost for the aggregator and EV owners,
- 2) develop a decentralized EMS i.e., CBS, for charge-discharge scheduling of EVs to minimize cost for EV owners,
- 3) present an economic analysis to compare the centralized and decentralized EMS strategies,
- 4) model the battery capacity degradation in EMSs to account for excessive charge-discharge cycles.

The paper is organized as follows: the system architecture of the proposed energy management framework is presented in section II, followed by the details of mathematical modelling of the proposed energy management systems in section III, the numerical validation is presented in section IV, results are presented in section V, discussion on the results is presented in VI, and VII concludes this paper.

II. SYSTEM ARCHITECTURE

Two strategies are developed for high density residential apartment buildings, the centralized strategy, and the decentralized strategy. In the centralized strategy referred here as the aggregator-based strategy (ABS), the aggregator is responsible for the fundamental data transactions between the

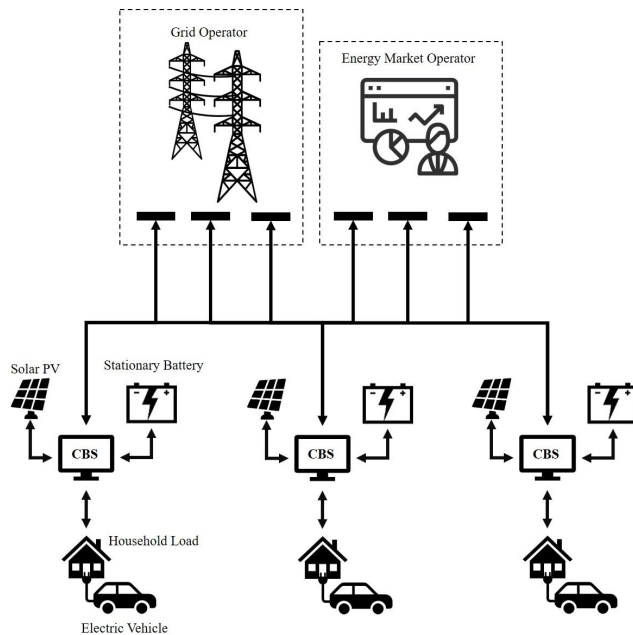


FIGURE 1. System architecture of the CBS.

individual household and the grid. Whereas, in the decentralized strategy, referred as the customer-based strategy (CBS), the individual household owner processes all energy transactions with the grid. However, the individual customer in CBS and the aggregator in ABS, do not take part in the energy market operations. The aggregator in ABS and the customers in CBS only provide grid support services. The energy market mechanism is beyond the scope of this study. An overview of the proposed EMS strategies is presented in figs. 1 and 2 for ABS and CBS, respectively. The architecture details of the proposed strategies are discussed in the following sub-sections.

A. CUSTOMER-BASED-STRATEGY

The objective for the customer-based-strategy (CBS) is to minimize the cost of electricity for the individual household energy consumers by optimally utilizing the flexibility of energy resources. It is assumed that each household has a separate smart meter installed which is capable of monitoring and controlling the flow of energy. Each household possess its own solar PV system, stationary battery, and an EV.

The energy and information flow process for the CBS is presented in fig. 1. The smart meter for respective household is capable of monitoring and controlling the energy flow based on the proposed CBS. Each smart meter communicates directly with the grid and optimizes the associated energy resources to minimize the cost of energy consumption for respective household. The day-ahead travel preferences of the EV owner is set in the EMS controller for each household. The EMS predicts the day-ahead load profiles of the household consumer and weather inputs for solar PV generation based on the historical time series dataset. Based on this information, the EMS determines the optimized

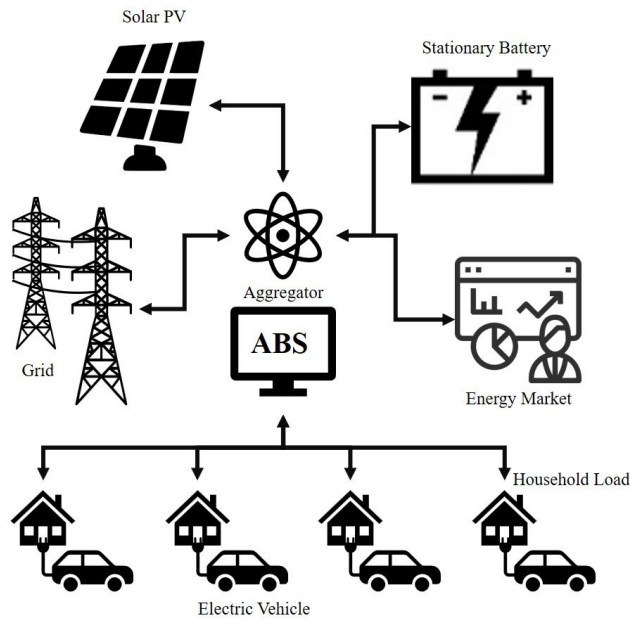


FIGURE 2. System architecture of the ABS.

charge-discharge schedules for the EV of individual household. The proposed CBS assumes that each residential household is managed by an independent EMS. The functionality for EV charge-discharge scheduling model is implemented on the individual EMS.

B. AGGREGATOR-BASED-STRATEGY

An aggregator is a grouping of agents in an electric power system to act as a single entity when engaging in energy markets or selling services to the grid operator [28]. Aggregators are capable of performing demand response operations and are responsible for the installation of respective monitoring & control systems (i.e., smart meters) and in some cases also the energy resources (i.e., solar PV, stationary batteries etc.) at end-user premises [29]. In this paper, the aggregator-based-strategy (ABS) is designed to minimize the aggregated cost of electricity for the apartment buildings unlike the CBS that minimized the cost for individual households. The aggregator owns and manages the solar PV and stationary battery systems.

The energy and information flow process for the ABS is presented in fig. 2. The aggregator is the central point of information flow in the proposed ABS, where the aggregator communicates with all the stake holders i.e., the households, the grid operator, and the energy market operator. The aggregator prepares the optimized schedule for charging-discharging of EVs and stationary battery storage while making the most of the intermittent renewable PV generation.

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 dataset. The proposed ABS assumes that each household is managed by a single aggregator. In addition, the aggregator has access to the historical time-series dataset 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 datasets. The aggregator then dispatches the charge-discharge scheduling of EVs based on mixed-integer programming model subject to grid constraints.

III. PROPOSED MODELS

The proposed EMSs schedule the charge-discharge of EVs in day-ahead stages and determines the energy supply and demand to minimize the cost of electricity. The proposed EMSs predict the household load, expected solar PV generation, EV distance travelled and EV availability using the prediction model presented in section III-A. The predicted parameters are then processed through the optimization model presented for both the strategies in section III-C. Figure 3 presents the process flow of the proposed methodology and the details of the proposed energy management strategies are presented in the following subsections.

A. PREDICTION MODEL

The day-ahead prediction of household load, solar generation and travel patterns allow optimal scheduling for charging/discharging of all energy storage units including stationary battery and the EV batteries. The day-ahead predictions are fed in the optimization model as input parameters to formulate the optimal schedule for charging and discharging of energy storage units considering all energy and travel demand constraints. This section presents the details of the methods used for predicting the input parameters for the optimization model of both strategies.

1) HOUSEHOLD LOAD DEMAND AND PV GENERATION

The artificial neural networks (ANN) are used to predict the parameters like household load and solar PV generation from historical time-series dataset. ANN is a reliable forecasting method in many applications including forecasting of household load, wind speed and weather [30]. A back-propagation learning algorithms is used in this paper which is commonly used algorithm in the feed-forward ANN. The forecast values, Z_t^i , can be expressed as:

$$Z_t^i = \sum_{j=1}^n \xi_{j} f \left(\omega_{0j} + \sum_{i=1}^x \omega_{ij} Z_{t-i}^i \right) + \varrho_t + \xi_0, \quad \forall t \in T \quad (1)$$

where $t \in \mathcal{L}_t$, \mathcal{K}_t represents the household load \mathcal{L}_t and solar PV generation \mathcal{K}_t . n is the number of hidden layers in the ANN model, the weights from the layers are indicated by ω_{ij} and ξ_j . The ϱ_t is a random shock, where ω_{0j} and ξ_0 represent the bias terms of the ANN. The subscript t represents the time of day.

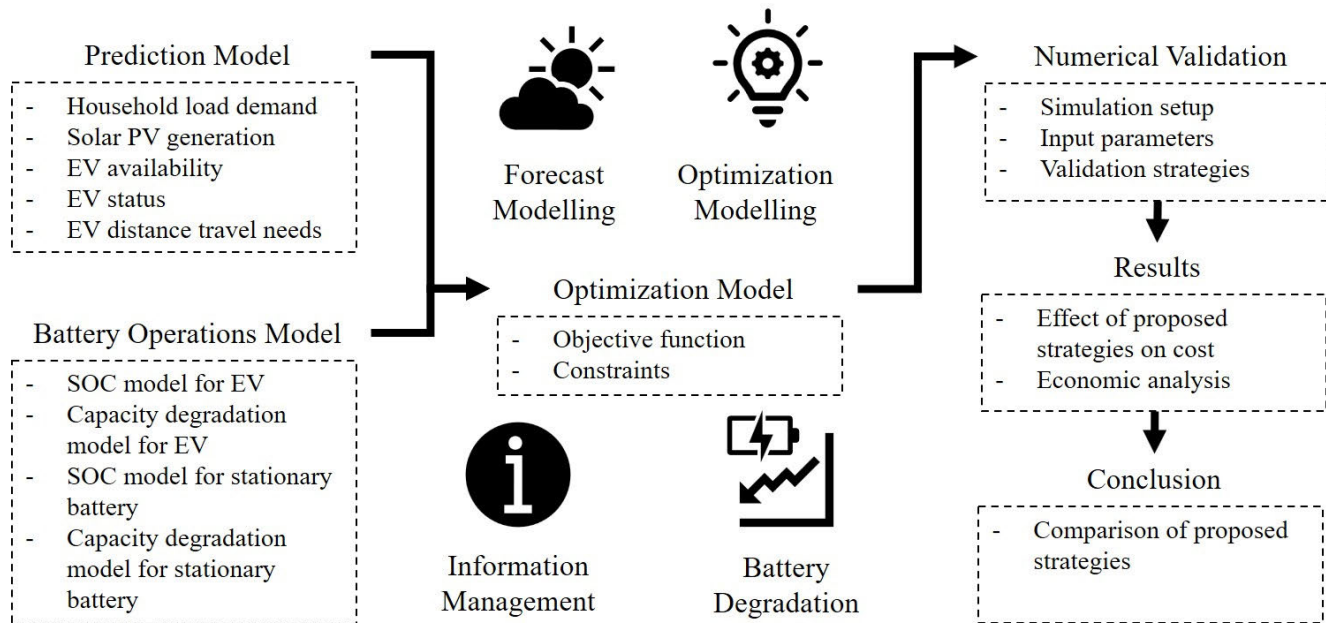


FIGURE 3. Process flow of the proposed energy management strategies.

2) EV AVAILABILITY

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:

$$A_t = f(t | \mathbb{N}_t, p_t) = \binom{\mathbb{N}_t}{p_t} p_t (1 - p_t)^{(\mathbb{N}_t - t)}, \quad \forall t \in T \quad (2)$$

where \mathbb{N}_t represents the number of scenarios for each EV to estimate the availability of an EV at home for charging/discharging and p_t is the success probability of the scenario. The status of the EV is estimated based on Algorithm 1. Four EV statuses have been identified for the EMSs: available, not available, departed, and arrived. The EV status identifies when a particular EV arrives home or departs from home to assign corresponding statuses. The status matrix is used to manage charge-discharge scheduling of EVs for upcoming trips.

3) EV DISTANCE TRAVEL

The daily commute distance of EVs for each household are estimated based on the PDFs developed from the historical time series dataset and is presented in eq. (3).

$$\mathbb{D}_t = f(t | \mu_t) = \frac{1}{\mu_t} e^{\left(\frac{-t}{\mu_t}\right)}, \quad \forall t \in T \quad (3)$$

where \mathbb{D}_t . The mean distance travelled by an EV are represented by μ_t respectively.

Algorithm 1 Status Matrix

```

1: for  $t \in T$  do
2:   if  $A_t = 1$  then
3:     if  $A_{t-1} = 0$  then
4:        $S_t = 3$  ▷ arrived
5:     else
6:        $S_t = 3$  ▷ available
7:     end if
8:   else
9:     if  $A_{t-1} = 1$  then
10:       $S_t = 4$  ▷ departed
11:    else
12:       $S_t = 2$  ▷ not available
13:    end if
14:  end if
15: end for
    
```

B. BATTERY MODEL

The operation of EV battery and the stationary battery are mathematically modelled in the following sub-sections.

1) EV BATTERY SOC MODELLING

The state-of-charge (SOC) of EVs for the day-ahead scheduling are generally modelled in eqs. (4) to (6). Here, δ_t^V represent the SOC of EV battery for time interval t . A_t is the binary availability matrix for EV. λ_t in eq. (5) is the SOC consumed due to distance travel by EVs when they are away from home. $\bar{\chi}^V$ represent the maximum capacity of the EV battery. The upper and lower bounds for the SOC of energy storage units are presented in eq. (11). $\bar{\mathbb{D}}_t$ represents the aggregated distance travel needs for upcoming trips and the SOC requirements to meet the travel needs are

constrained in eq. (8).

$$\delta_t^V = \delta_{t-1}^V + \frac{\eta_c^V \mathcal{V}_t^c \Delta t}{\bar{\chi}^V} - \frac{\mathcal{V}_t^d \Delta t}{\eta_d^V \bar{\chi}^V}, \quad \iff \mathbb{A}_t = 1 \quad (4)$$

$$\delta_t^V = \delta_{t-1}^V - \lambda_t, \quad \iff \mathbb{A}_t = 0, \quad \forall t \in T$$

$$\lambda_t = \frac{\mathbb{E}^V \mathbb{D}_t}{\bar{\chi}^V}, \quad \forall t \in T \quad (5)$$

$$\underline{\delta}_V \geq \delta_t^V \leq \bar{\delta}_V, \quad \forall t \in T \quad (6)$$

$$\delta_t^V = \frac{\mathbb{E}^V \bar{\mathbb{D}}_t}{\bar{\chi}^V}, \quad \iff \mathbb{S}_t = 4, \quad \forall t \in T \quad (7)$$

The state of charge of EV batteries is modelled in eq. (4). The model considers the lower and upper bounds of battery state of charge to optimize the effective battery life eq. (7). \mathbb{E}^V & \mathbb{D}_t represent the efficiency of EV batteries in kWh/km and distance travelled by EVs while they are away from home, respectively. η_c^V & η_d^V represent the charging-discharging efficiencies of the EV charger, respectively. The model also has the flexibility to prioritize the travel needs of the consumers eqs. (5) and (6).

2) EV BATTERY CAPACITY DEGRADATION MODELLING

Battery capacity degradation is a phenomenon observed in rechargeable batteries which causes decrease in the amount of charge that a battery can deliver at the rated voltage over the period. This phenomenon is modelled to account for the cost associated with the capacity degradation, so that the V2G flexibilities are not exploited. The battery capacity degradation for EV battery is estimated based on the work done by authors in [31] and is replicated in eqs. (9) and (10).

$$\Pi_t^V = (\gamma_1 v + \gamma_3 v^2 + \gamma_5 v^3 + \gamma_7 v^4) + (\gamma_2 + \gamma_6 v) |\mathcal{V}_t^{c \rightleftharpoons d}| + \frac{\gamma_4}{v} |\mathcal{V}_t^{c \rightleftharpoons d}|^2, \quad \forall t \in T \quad (8)$$

$$\partial_t^V = \mathbb{A}_t \Pi_t^V \theta^V, \quad \forall t \in T \quad (9)$$

The cost of battery capacity degradation is modelled in eqs. (9) and (10) for the EV. Here Π_t^V represents the battery capacity degradation in kWh , θ^V is the cost of battery degradation in $\$/Wh$, v is the battery voltage in *volts* and γ is the battery degradation coefficient.

3) STATIONARY BATTERY SOC MODELLING

The SOC of stationary battery for the day-ahead scheduling are generally modelled in eqs. (11) and (12). Here, δ_t^B represent the SOC of stationary battery storage for time interval t . $\bar{\chi}^B$ represent the maximum capacity of the stationary battery. The upper and lower bounds for the SOC of stationary energy storage are presented in eq. (12).

$$\delta_t^B = \delta_{t-1}^B + \frac{\eta_c^B \mathcal{B}_t^c \Delta t}{\bar{\chi}^B} - \frac{\mathcal{B}_t^d \Delta t}{\eta_d^B \bar{\chi}^B}, \quad \forall t \in T \quad (10)$$

$$\underline{\delta}_B \geq \delta_t^B \leq \bar{\delta}_B, \quad \forall t \in T \quad (11)$$

The state of charge of EV batteries is modelled in eq. (4). The model considers the lower and upper bounds of battery

state of charge to optimize the effective battery life eq. (7). η_c^B & η_d^B represent the charging-discharging efficiencies of the stationary battery charger, respectively. The model also has the flexibility to prioritize the travel needs of the consumers eqs. (5) and (6).

4) STATIONARY BATTERY CAPACITY DEGRADATION MODELLING

The battery capacity degradation for the stationary battery storage is estimated based on the work done by authors in [31] and is replicated in eqs. (13) and (14).

$$\Pi_t^B = (\gamma_1 v + \gamma_3 v^2 + \gamma_5 v^3 + \gamma_7 v^4) + (\gamma_2 + \gamma_6 v) |\mathcal{B}_t^{c \rightleftharpoons d}| + \frac{\gamma_4}{v} |\mathcal{B}_t^{c \rightleftharpoons d}|^2, \quad \forall t \in T \quad (12)$$

$$\partial_t^B = \Pi_t^B \theta^B, \quad \forall t \in T \quad (13)$$

The cost of battery capacity degradation is modelled in eqs. (13) and (14) for the stationary battery. Here Π_t^B represents the battery capacity degradation in kWh , θ^B is the cost of battery degradation in $\$/Wh$, v is the battery voltage in *volts* and γ is the battery degradation coefficient.

C. OPTIMIZATION MODEL

The optimization model is designed to minimize the cost of electricity. The details of optimization modelling are presented in the following subsections.

1) OBJECTIVE FUNCTION

The objective for both the strategies i.e., ABS and CBS, is to minimize the cost of electricity for the energy consumers by optimally utilizing the energy resources. Therefore, the objective function for both the strategies is same and expressed mathematically as eq. (15).

$$\min \sum_{t \in T} \left(\underbrace{\alpha_t \pi_t^+ \mathcal{P}_t \Delta t}_{\text{cost(energy bought)}} + \underbrace{\beta_t \pi_t^- \mathcal{P}_t \Delta t}_{\text{cost(energy sold)}} + \underbrace{\partial_t^B + \partial_t^V}_{\text{cost(degradation)}} \right) \quad (14)$$

where \mathcal{P} is the net power flow from/to the grid during time interval t . α & β are the auxiliary binary variables. π_t^+ and π_t^- are the energy tariffs for buying and selling energy from/to the grid, respectively. Δt is the time interval.

2) POWER FLOW CONSTRAINTS - CBS

The power balance equation for individual household is presented in eq. (16).

$$\mathcal{P}_t = \mathcal{L}_t + \mathcal{V}_t^c - \mathcal{V}_t^d + \mathcal{B}_t^c - \mathcal{B}_t^d - \mathcal{K}_t, \quad \forall t \in T \quad (15)$$

where \mathcal{L}_t is the household load. \mathcal{K}_t represents the solar PV generation power. \mathcal{B}_t^c & \mathcal{B}_t^d are the charging-discharging power of stationary battery storage managed by individual household, respectively. \mathcal{V}_t^c & \mathcal{V}_t^d represent the charging-discharging power of EV for individual household, respectively.

3) POWER FLOW CONSTRAINTS - ABS

The power balance equation for the aggregator is presented in eq. (17).

$$\mathcal{P}_t = \mathcal{B}_t^c - \mathcal{B}_t^d - \mathcal{K}_t + \sum_{i \in T} (\mathcal{L}_{(t,h)} + \mathcal{V}_{(t,h)}^c - \mathcal{V}_{(t,h)}^d) \quad \forall t \in T, \forall h \in H \quad (16)$$

where $\mathcal{L}_{(t,h)}$ is the household load, \mathcal{K}_t is the solar PV generation power. \mathcal{B}_t^c & \mathcal{B}_t^d are the charging-discharging power of stationary battery storage respectively, managed by the aggregator, $\mathcal{V}_{(t,h)}^c$ & $\mathcal{V}_{(t,h)}^d$ are the charging-discharging power of EV for individual household, respectively. The subscripts t & h represent the time interval and individual household, respectively.

4) AUXILIARY CONSTRAINTS

α_t and β_t are the auxiliary binary variables for power drawn from the grid and power supplied back to the grid, respectively. eqs. (18) and (21) are the constraints to optimize the power drawn by individual household from the grid. \mathcal{P} is positive when $\alpha = 1$ & $\beta = 0$ for energy purchase from the grid. In other case, \mathcal{P} is negative when $\alpha = 0$ & $\beta = 1$ for energy sold to the grid.

$$\alpha_t + \beta_t = 1, \quad \forall t \in T \quad (17)$$

$$\alpha_t \beta_t = 0, \quad \forall t \in T \quad (18)$$

$$\alpha_t \mathcal{P}_t \geq 0, \quad \forall t \in T \quad (19)$$

$$\beta_t \mathcal{P}_t \leq 0, \quad \forall t \in T \quad (20)$$

IV. NUMERICAL VALIDATION

Simulation studies are conducted to compare and validate the adequacy of the proposed strategies for minimizing cost of electricity for energy consumers. This section discusses the input parameters used for simulation studies.

A. SIMULATION SETUP

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 section III-C is formulated in the GAMS and solved using a commercially available solver i.e., Baron [32], with zero relative and absolute optimality gap. 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 GAMS and MATLAB.

1) ANN PREDICTION MODEL

The prediction model generates day-ahead household load and solar PV generation for 20 households using the artificial neural network (ANN). The MATLAB neural network toolbox (nntool) has been used to train the feed forward ANNs. MATLAB provides built in 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 [30].

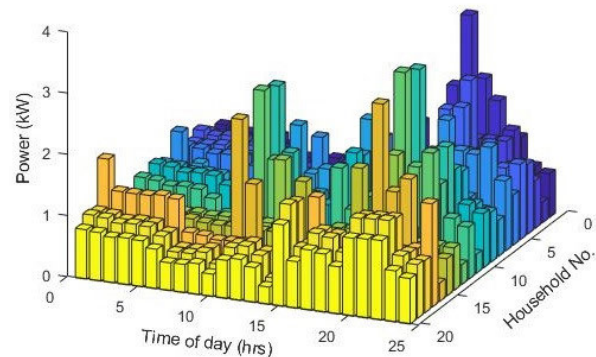


FIGURE 4. Household load.

The prediction model uses a three-layered feed-forward neural network trained by the Levenberg-Marquardt (LM) algorithm. LM is most effective in identifying the minimum of a convex objective function as it combines the robustness of the steepest-descent method with the quadratic convergence rate of the Gauss-Newton method. It outperforms gradient descent and conjugate gradient methods for medium sized nonlinear models. 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.

2) APARTMENT BUILDING LOAD

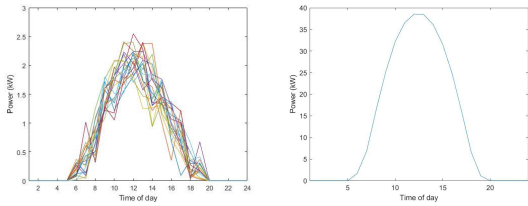
The proposed strategies are assessed by means of simulations on a high-density residential building in Sydney, Australia. The five levels building consists of 20 households in total with underground parking space. The parameters for prediction model are extracted from the load profile dataset of a residential neighbourhood in Sydney used by [15]. The prediction model generates day-ahead household load for the 20 households. The load profiles for 20 households are presented in fig. 4.

3) SOLAR PV SYSTEM

The solar PV generation profiles are synthetically generated using the tool developed by [33]. The peak power of the solar system for the ABS is assumed to be 45.78 kWp and 2.29 kWp for individual households in case of CBS. The efficiency for the DC to AC inverter is assumed to be 95%. The solar PV generation profiles of individual households for CBS are presented in fig. 5a. The solar PV generation profile for the aggregator in ABS is presented in fig. 5b.

4) ENERGY TARIFF

The time of use tariff (TOU) and the cumulative household load are taken from [34] and presented in fig. 6. C_p & C_s represent the energy tariff for buying and selling energy. HL represent the cumulative household load.



(a) Solar PV generation profiles of individual households for CBS (b) Solar PV generation profile for ABS

FIGURE 5. Solar PV generation profiles.

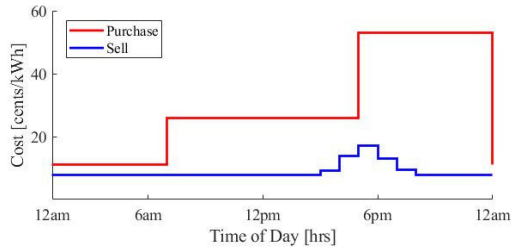


FIGURE 6. Energy tariff and cumulative household load.

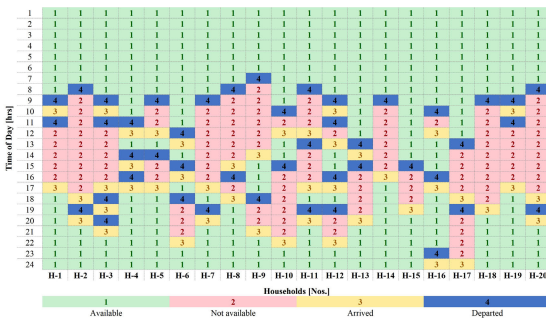


FIGURE 7. EV availability/status matrix for each household.

5) EV SPECIFICATIONS AND TRAVEL PATTERNS

Each household is assumed to have a designated parking space with a Level-1, bidirectional EV charger at 220 V, 15 A, 3 kW charging/discharging power as used by authors in [35]. For simplicity, a mid-range V2G capable EV is considered 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 [34]. The initial and final SOC of stationary battery and the EVs are considered the same to model the continuity. The travel pattern of EVs for each household is presented in fig. 7 in the form of status matrix.

6) STATIONARY BATTERY STORAGE

Each household is assumed to have installed a stationary battery with 10 kWh capacity in case of CBS. Each household have a charger with 3 kW charging-discharging capacity, 230 VAC @ 50 Hz frequency and 50 VDC (internal battery voltage). However, in case of ABS the aggregator manages the solar PV generation and stationary battery. The installed capacity of stationary battery is 200 kWh with 60 kW charging-discharging capacity.

B. ENERGY MANAGEMENT STRATEGIES

In light of the inputs discussed in the previous sections, the numerical simulations are conducted for the proposed strategies. Likewise, to compare the effectiveness of the proposed strategies, the outcomes are compared with the respective uncoordinated charging strategies.

C. UNCOORDINATED (ABS)

The uncoordinated charging strategy for the centralized energy management scheme i.e., ABS, does not consider the utilization of EVs for V2G flexibilities. In this strategy, the EVs are assumed to plug-in for charging as they arrive home, regardless of the energy tariff. The solar PV generation is utilized to charge the stationary battery and the grid power charges the stationary battery in the off-peak load hours only, when the tariff for buying energy is minimum. The aggregator does not sell energy back to the grid in this strategy. The methodology for uncoordinated charging is mathematically modelled as:

$$Cost = \sum_{t \in T} (\pi_t^+ P_t \Delta t + \partial_t^B + \partial_t^V), \quad \forall t \in T \quad (21)$$

subject to:

$$P_t = \mathcal{B}_t^c - \mathcal{K}_t + \sum_{h \in H} (\mathcal{L}_{(t,h)} + \mathcal{V}_{(t,h)}^c) \iff ABS \quad (22)$$

$$\forall t \in T, \forall h \in H$$

Equations (4) to (12), eqs. (9) to (14)

D. UNCOORDINATED (CBS)

The uncoordinated charging strategy for the decentralized energy management scheme i.e., CBS, also does not consider the utilization of EVs for V2G flexibilities. In this strategy, the EVs are assumed to plug-in as they reach home, regardless of the energy tariff. The solar PV generation is utilized to charge the stationary battery and the grid power charges the stationary battery in the off-peak load hours only, when the tariff for buying energy is minimum. Energy is not sold back to the grid in this strategy. The methodology for uncoordinated charging is mathematically modelled as:

$$Cost = \sum_{t \in T} (\pi_t^+ P_t \Delta t + \partial_t^B + \partial_t^V), \quad \forall t \in T \quad (23)$$

subject to:

$$P_t = \mathcal{L}_t + \mathcal{V}_t^c + \mathcal{B}_t^c - \mathcal{K}_t \iff CBS \quad (24)$$

$$\forall t \in T$$

Equations (4) to (12), eqs. (9) to (14)

V. RESULTS

Based on the input data, the EMSs assesses the needs of individual household and creates a day-ahead optimization schedule to minimize the cost for individual households in CBS and for the aggregator in ABS.

TABLE 1. Aggregated cost and energy summary for energy management strategies.

	Energy Management Strategies			
	ABS (optimized)	ABS (uncoordinated)	CBS (optimized)	CBS (uncoordinated)
Aggregated cost of electricity	127.7	294.4	139.1	336.2
Aggregated Energy	1,637.2	2,675.5	1,637.2	2,675.5

A. EFFECT OF PROPOSED EMSs ON COST

The results show significant reduction in cost of energy consumption for both, centralized and decentralized energy management strategies, through optimal management of the energy resources. Table 1 presents the summary of cost comparison between the proposed strategies and their respective uncoordinated strategies.

1) OPTIMIZED (ABS) VS UNCOORDINATED (ABS)

It can be noted from table 1 that the optimized (ABS) consumes almost 39% less net energy compared to the uncoordinated (ABS), while fulfilling all the EV travel needs. The cost savings for the optimized (ABS) compared to the uncoordinated (ABS) are 57%.

2) OPTIMIZED (CBS) VS UNCOORDINATED (CBS)

The results presented in table 1 show that the optimized (CBS) consumes almost 39% less net energy compared to the uncoordinated (CBS), while fulfilling all the energy needs of individual households including the EV travel needs. The cost savings for the optimized (CBS) compared to the uncoordinated (CBS) are 59%.

3) UNCOORDINATED (ABS) VS UNCOORDINATED (CBS)

It can be noted from the results presented in Table 1, that the uncoordinated (ABS) and the uncoordinated (CBS), both strategies consume equal net energy to fulfill the energy needs of individual households including the EV travel needs. However, it can be noted that the cost savings for the uncoordinated (ABS) are 12% higher compared to the uncoordinated (CBS).

4) OPTIMIZED (ABS) VS OPTIMIZED (CBS)

The results presented in table 1 show that the optimized (ABS) and the optimized (CBS), both strategies consume equal net energy to fulfill all the energy demands including the EV travel needs. However, it can be noted that the cost savings for the optimized (ABS) are 8% higher compared to the optimized (CBS).

B. ECONOMIC ANALYSIS

Economic analysis for the proposed strategies was conducted and the results are presented in table 2. Here for simplicity, we have assumed the cost of infrastructure (i.e., solar PV system, battery storage etc.) for implementing both the strategies are same. The pay-back periods for the proposed strategies were evaluated and it can be seen that the payback period for the optimized (ABS) proved to be better than the optimized (CBS). The payback period is less than the life of the solar

TABLE 2. Economic Analysis.

Parameters	ABS	CBS
Solar PV panel cost	\$525	\$525
Total no. of solar PV panels	140	140
Total cost of solar PV panels	\$73,500	\$73,500
Stationary battery unit cost	\$8,000	\$8,000
Total no. of stationary battery units	20	20
Total cost of stationary battery units	\$160,000	\$160,000
Daily cost savings	\$167	\$155
Yearly cost savings	\$60,861	\$56,699
Payback Period (Years)	3.8	4.1

PV and stationary battery storage. Hence, the investment in the infrastructure will be economically feasible.

VI. DISCUSSION

This paper presents two optimization strategies (i.e., CBS and ABS). The expected savings resulting from their application were evaluated numerically for realistic scenarios. The cost of energy consumption was minimized without compromising the travel needs of EV owners by optimal utilization of the available energy resources, which also resulted in a reduction in energy drawn from the electric power grid. Comparison of the proposed strategies with their respective un-optimized strategies and between each other, showed that the centralized strategy i.e., ABS, is more effective in reducing the cost of energy than the decentralized strategy i.e., CBS. This is partly due to the fact that the aggregator has bulk energy available in terms of aggregated energy storage and has the flexibility to exploit the energy arbitrage. The proposed strategies not only reduce the cost of energy consumption but also reduce the energy drawn from the grid. However, in terms of reducing the energy demand from the grid, both the strategies show similar results.

The mathematical formulation of the proposed strategies is non-linear, that could result in extensive computational time and can be linearized for scalable solutions, but in the context presented in this paper it was not appropriate. However, if this approach is applied to micro-grid with reasonably large number of energy players, the model could be linearized for time efficient solutions without having any impact on the main results. The proposed optimization strategies were validated using time-of-use (TOU) tariffs, but they are expected to work equally well with other tariffs, and the centralized strategy, i.e., ABS, is expected to be superior to the decentralized strategy i.e., CBS, under all circumstances. Another limitation of the proposed methodology is the lack of uncertainty modelling for predicted parameters. However, the inclusion of uncertainty modelling will not change the main conclusion drawn from this study i.e., the centralized management of

energy resources (ABS) is more cost effective compared to the decentralized management of energy resources (CBS). In addition, the proposed model could also be validated for seasonal changes in input parameters like household load profiles, solar PV generation and travel patterns.

The future work will consider uncertainty modelling of the predicted parameters along with validation of the robustness of the proposed EMS with seasonal changes in input parameters. The proposed models also lacked a framework for peer-to-peer (P2P) energy trading. Therefore, the future work will also focus on developing a comprehensive P2P energy trading framework for effective management of energy resources. Nevertheless, the results of current study show enough evidence to claim that the centralized management of energy resources (ABS) is more effective compared to the decentralized management of energy resources (CBS), in terms of cost savings and reduction in energy consumption for individual energy.

VII. CONCLUSION

Two energy management strategies i.e., CBS and ABS, for EV charge-discharge scheduling were proposed in this paper to minimize the cost of electricity in a high-density residential apartment building. The strategies were compared to investigate their effectiveness in terms of cost savings and reduction in energy demand for energy consumers. The simulation results indicate that the centralized EMS i.e., ABS, is more effective compared to the decentralized EMS i.e., CBS, in terms of cost savings. It is also observed that the energy management strategies reduce the energy drawn from the grid by 39% compared to un-optimized energy management schemes. However, the proposed EMSs lacked in modelling the expected cost of uncertainty due to predicted parameters in addition to extensive validation of the proposed EMSs with the seasonally varying input parameters. Detailed modelling of energy trading framework is also missing in the proposed models. Therefore, future work will focus on developing a comprehensive energy management system that accounts for P2P energy trading framework, models the expected cost of uncertainty along with detailed validation with diverse range of data inputs to account for seasonal variations.

REFERENCES

- [1] P. Nejat, F. Jomehzadeh, M. M. Taheri, M. Gohari, and M. Z. A. Majid, "A global review of energy consumption, CO₂ emissions and policy in the residential sector (with an overview of the top ten CO₂ emitting countries)," *Renew. Sustain. Energy Rev.*, vol. 43, pp. 843–862, Mar. 2015, doi: 10.1016/j.rser.2014.11.066.
- [2] IEA (International Energy Agency). (2012). *ETP-Energy Technology Perspectives 2012*. [Online]. Available: http://www.iea.org/publications/freepublications/publication/ETP2012_free.pdf
- [3] ERTRAC European Technology Platforms. (Jun. 2012). *European Roadmap Electrification of Road Transport*. [Online]. Available: https://www.ertrac.org/uploads/documentsearch/id31/electrification_roadmap_june2012_62.pdf
- [4] J. Van Roy, N. Leemput, F. Geth, R. Salenbien, J. Buscher, and J. Driesen, "Apartment building electricity system impact of operational electric vehicle charging strategies," *IEEE Trans. Sustain. Energy*, vol. 5, no. 1, pp. 264–272, Jan. 2014. [Online]. Available: <https://ieeexplore-ieee.org/simsrad.net.ocs.mq.edu.au/document/6650062>
- [5] S. Li, H. He, Y. Chen, M. Huang, and C. Hu, "Optimization between the PV and the retired EV battery for the residential microgrid application," *Energy Procedia*, vol. 75, pp. 1138–1146, Aug. 2015.
- [6] N. Odokhuu, K.-B. Lee, M. A. Ahmed, and Y.-C. Kim, "Optimal energy management of V2B with RES and ESS for peak load minimization," *Appl. Sci.*, vol. 8, no. 11, p. 2125, Nov. 2018.
- [7] Q. Yan, B. Zhang, and M. Kezunovic, "Optimized operational cost reduction for an EV charging station integrated with battery energy storage and PV generation," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2096–2106, Mar. 2019.
- [8] J. P. Sausen, M. F. B. Binelo, M. D. Campos, A. T. Z. R. Sausen, and P. S. Sausen, "Economic feasibility study of using an electric vehicle and photovoltaic microgeneration in a smart home," *IEEE Latin Amer. Trans.*, vol. 16, no. 7, pp. 1907–1913, Jul. 2018.
- [9] H. Kikusato, K. Mori, S. Yoshizawa, Y. Fujimoto, H. Asano, Y. Hayashi, A. Kawashima, S. Inagaki, and T. Suzuki, "Electric vehicle charge-discharge management for utilization of photovoltaic by coordination between home and grid energy management systems," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3186–3197, May 2019.
- [10] G. R. C. Mouli, M. Kefayati, R. Baldick, and P. Bauer, "Integrated PV charging of EV fleet based on energy prices, V2G, and offer of reserves," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1313–1325, Mar. 2019.
- [11] S. Han, H. Aki, S. Han, B. Kwon, and J.-B. Park, "Optimal charging strategy for a residential PEV battery considering bidirectional trade and frequency regulation," *Int. J. Control, Autom. Syst.*, vol. 14, no. 2, pp. 587–597, Apr. 2016.
- [12] G. S. Georgiou, P. Christodoulides, A. Georgiou, and S. A. Kalogirou, "A linear programming approach to the optimal utilization of renewable energy sources in buildings," in *Proc. 52nd Int. Universities Power Eng. Conf. (UPEC)*, Aug. 2017, pp. 1–6.
- [13] R. K. Bonthu, H. Pham, R. P. Aguilera, and Q. P. Ha, "Minimization of building energy cost by optimally managing PV and battery energy storage systems," in *Proc. 20th Int. Conf. Electr. Mach. Syst. (ICEMS)*, Aug. 2017, pp. 1–6.
- [14] V. Kiray, T. Topal, L. Şağbanşua, and I. Atacak, "A modelling study of renewable and stored energy sharing and pricing management system developed for multi-apartment complexes," in *Proc. IEEE PES Innov. Smart Grid Technol., Eur.*, Oct. 2014, pp. 1–6.
- [15] M. S. H. Nizami, M. J. Hossain, K. Mahmud, and J. Ravishankar, "Energy cost optimization and DER scheduling for unified energy management system of residential neighborhood," in *Proc. IEEE Int. Conf. Environ. Electr. Eng. IEEE Ind. Commercial Power Syst. Eur. (EEEIC / I CPS Europe)*, Jun. 2018, pp. 1–6.
- [16] J. Van Roy, N. Leemput, F. Geth, J. Buscher, R. Salenbien, and J. Driesen, "Electric vehicle charging in an office building microgrid with distributed energy resources," *IEEE Trans. Sustain. Energy*, vol. 5, no. 4, pp. 1389–1396, Oct. 2014.
- [17] H. K. Nguyen and J. B. Song, "Optimal charging and discharging for multiple PHEVs with demand side management in vehicle-to-building," *J. Commun. Netw.*, vol. 14, no. 6, pp. 662–671, Dec. 2012.
- [18] M. Khoshjahan, M. Soleimani, and M. Kezunovic, "Optimal participation of PEV charging stations integrated with smart buildings in the wholesale energy and reserve markets," in *Proc. IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (ISGT)*, Feb. 2020, pp. 1–5.
- [19] J. Li, Z. Wu, S. Zhou, H. Fu, and X.-P. Zhang, "Aggregator service for PV and battery energy storage systems of residential building," *CSEE J. Power Energy Syst.*, vol. 1, no. 4, pp. 3–11, Dec. 2015.
- [20] C. Cao, M. Cheng, and B. Chen, "Optimal scheduling of PEV charging/discharging in microgrids with combined objectives," *Smart Grid Renew. Energy*, vol. 7, no. 4, p. 115, 2016.
- [21] A. Kawashima, T. Yamaguchi, R. Sasaki, S. Inagaki, T. Suzuki, and A. Ito, "Apartment building energy management system in group optimization with electricity interchange using in-vehicle batteries," *SICE J. Control, Meas., Syst. Integr.*, vol. 8, no. 1, pp. 52–60, Jan. 2015.
- [22] A. Kawashima, R. Sasaki, T. Yamaguchi, S. Inagaki, A. Ito, and T. Suzuki, "Energy management systems based on real data and devices for apartment buildings," in *Proc. IECON-41st Annu. Conf. IEEE Ind. Electron. Soc.*, Nov. 2015, pp. 003212–003217.
- [23] A. Ito, A. Kawashima, T. Suzuki, S. Inagaki, T. Yamaguchi, and Z. Zhou, "Model predictive charging control of in-vehicle batteries for home energy management based on vehicle state prediction," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 1, pp. 51–64, Jan. 2018.
- [24] S. Yoon, K. Park, and E. Hwang, "Connected electric vehicles for flexible vehicle-to-grid (V2G) services," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2017, pp. 411–413.

- [25] J. Torres-Moreno, A. Gimenez-Fernandez, M. Perez-Garcia, and F. Rodriguez, "Energy management strategy for micro-grids with PV-battery systems and electric vehicles," *Energies*, vol. 11, no. 3, p. 522, Feb. 2018.
- [26] S. Rafique, M. Nizami, U. Irshad, M. Hossain, and G. Town, "A customer-based-strategy to minimize the cost of energy consumption by optimal utilization of energy resources in an apartment building," in *Proc. IOP Conf. Ser., Earth Environ. Sci.*, vol. 322, Sep. 2019, Art. no. 012018. [Online]. Available: <https://iopscience.iop.org/article/10.1088/1755-1315/322/1/012018>
- [27] S. Rafique, M. S. H. Nizami, U. B. Irshad, J. Hossain, and G. Town, "An aggregator-based-strategy to minimize the cost of energy consumption by optimal utilization of energy resources in an apartment building," in *Proc. IEEE Int. Conf. Environ. Electr. Eng. IEEE Ind. Commercial Power Syst. Eur. (EEEIC / I CPS Europe)*, Jun. 2019, pp. 1–5.
- [28] S. Burger, J. P. Chaves-Avila, C. Batlle, and I. J. Pérez-Arriaga, "The value of aggregators in electricity systems," MIT Center Energy Environ. Policy Res., Tech. Rep. CEEPR WP 2016-001, 2016. [Online]. Available: https://energy.mit.edu/wp-content/uploads/2016/01/CEEPR_WP_2016-001.pdf
- [29] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, "The role of aggregators in smart grid demand response markets," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1247–1257, Jul. 2013.
- [30] F. Rodrigues, C. Carreira, and J. M. F. Calado, "The daily and hourly energy consumption and load forecasting using artificial neural network method: A case study using a set of 93 households in Portugal," *Energy Procedia*, vol. 62, pp. 220–229, 2014. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1876610214034146>, doi: [10.1016/j.egypro.2014.12.383](https://doi.org/10.1016/j.egypro.2014.12.383).
- [31] M. N. Mojdehi and P. Ghosh, "Estimation of the battery degradation effects on the EV operating cost during Charging/Discharging and providing reactive power service," in *Proc. IEEE 81st Veh. Technol. Conf. (VTC Spring)*, May 2015, pp. 1–5.
- [32] M. Tawarmalani and N. V. Sahinidis, "A polyhedral branch-and-cut approach to global optimization," *Math. Program.*, vol. 103, no. 2, pp. 225–249, Jun. 2005.
- [33] S. Pfenninger and I. Staffell, "Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data," *Energy*, vol. 114, pp. 1251–1265, Nov. 2016.
- [34] S. Rafique and G. Town, "Aggregated impacts of electric vehicles on electricity distribution in New South Wales, Australia," *Austral. J. Electr. Electron. Eng.*, vol. 14, nos. 3–4, pp. 71–87, Oct. 2017.
- [35] S. Rafique and G. E. Town, "Potential for electric vehicle adoption in Australia," *Int. J. Sustain. Transp.*, vol. 13, no. 4, pp. 245–254, Apr. 2019.



SOHAIB RAFIQUE (Student Member, IEEE) received the B.E. and M.E.M. degree in electrical engineering from the NED University of Engineering and Technology, Karachi, Pakistan, in 2008 and 2013, respectively, and the M.Res. degree from Macquarie University, Sydney, NSW, Australia, in 2016, where he is currently pursuing the Ph.D. degree in electrical engineering. From 2009 to 2015, he has worked the electric power utility and oil and gas industries. He received prestigious Australian Government Research Training Program Scholarship in 2016/17 for M.Res. and 2017/18 for Ph.D. His research is focused on developing energy management systems for energy consumers in distribution network integrated with distributed energy resources and electric vehicles. His research interests include demand response, optimization and energy management systems for active distribution networks, electric vehicles, and demand side management.



MOHAMMAD JAHANGIR HOSSAIN (Senior Member, IEEE) received the B.Sc. and M.Sc.Eng. degrees in electrical and electronic engineering from the Rajshahi University of Engineering and Technology (RUET), Bangladesh, in 2001 and 2005, respectively, and the Ph.D. degree in electrical and electronic engineering from the University of New South Wales, Australia, in 2010. He is

currently an Associate Professor with the School of Electrical and Data Engineering, University of Technology Sydney, Australia. He worked as an Associate Professor with the School of Engineering, Macquarie University, a Senior Lecturer and a Lecturer with the Griffith School of Engineering, Griffith University, Australia, for a period of five years, and as a Research Fellow with the School of Information Technology and Electrical Engineering, The University of Queensland, Brisbane, QLD, Australia. His research interests include renewable energy integration and stabilization, voltage stability, micro grids and smart grids, robust control, electric vehicles, building energy management systems, and energy storage systems.



MOHAMMAD SOHRAB HASAN NIZAMI (Member, IEEE) received the B.Sc. degree in electrical and electronic engineering from the Islamic University of Technology, Dhaka, Bangladesh, in 2010, the M.Sc. degree in sustainable energy technology from the Eindhoven University of Technology (TU/e), The Netherlands, in 2015, and the Ph.D. degree in electrical engineering from Macquarie University, Sydney, NSW, Australia, in 2020. His research is focused on transactive energy-based management and optimization of distributed energy resources in distribution networks. His research interests include grid interactive demand response, optimization and energy management systems for active distribution network, electric vehicles, demand side management, and transactive energy management.



USAMA BIN IRSHAD (Student Member, IEEE) received the B.Sc. degree in electrical (power) engineering from the COMSATS Institute of Information Technology, Pakistan, in 2012, and the M.Sc. degree in electrical engineering from the King Fahd University of Petroleum and Minerals, Saudi Arabia. He is currently pursuing the Ph.D. degree in science and engineering with Macquarie University, Australia. His research interests include power systems, electric vehicles, energy storage systems, optimization and control, integration of renewable energy sources, and intelligent control systems.



SUBHAS CHANDRA MUKHOPADHYAY (Fellow, IEEE) received the B.E.E., M.E.E., Ph.D. degrees in India and the D.Eng. degree in Japan. He has over 30 years of teaching, industrial, and research experience. He is currently a Professor of mechanical/electronics engineering with Macquarie University, Australia, and the Discipline Leader of the Mechatronics Engineering Degree Programme. He has supervised over 40 master's students and over 100 Honors students. He has examined over 60 master's thesis. He has published over 400 papers in different international journals and conference proceedings, authored nine books and 42 book chapters, and edited 18 conference proceedings. He has also edited 32 books with Springer Verlag and 25 journal special issues. He has delivered 355 presentations, including keynote, invited, tutorial, and special lectures. His current research interests include smart sensors and sensing technology, instrumentation techniques, wireless sensors and network (WSN), the Internet of Things (IoT), and so on. He is a Fellow of IET, U.K., and IETE, India. He received the Gold Medal for his B.E.E. degree. He has organized over 20 international conferences as either General Chair/Co-chair or Technical Programme Chair. He chairs the IEEE NSW Sensors Council chapter. He is a Topical Editor of the IEEE SENSORS JOURNAL. He is also an Associate Editor of the IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENTS. He is a Distinguished Lecturer of the IEEE Sensors Council, during 2017–2022.

...