IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 12, 2020, accepted February 24, 2020, date of publication February 27, 2020, date of current version March 6, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2976710

An Optimal Scheduling and Distributed Pricing Mechanism for Multi-Region Electric Vehicle Charging in Smart Grid

MUHAMMAD BABAR RASHEED[1], MUHAMMAD AWAIS[2], THAMER ALQUTHAMI[3], AND IRFAN KHAN[4], (Member, IEEE)

[1]Department of Electronics and Electrical Systems, The University of Lahore, Lahore 54000, Pakistan
[2]Department of Technology, The University of Lahore, Lahore 54000, Pakistan
[3]Electrical and Computer Engineering Department, King Abdulaziz University, Jeddah 21589, Saudi Arabia
[4]Marine Engineering Technology Department in a joint appointment with the Electrical and Computer Engineering Department, Texas A&M University, Galveston, TX 77553-1675, USA

Corresponding author: Muhammad Babar Rasheed (babarmeher@gmail.com)

This work was supported by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under Grant D-130-135-1441.

ABSTRACT Despite the universal importance of price based demand response (DR) for managing electric vehicle (EV) charging load, the academic literature has explored various mechanisms to its implementation. The prequel to this work has demonstrated that implementation of load management schemes on the basis of price based DR programs leads to costlier scheduling for low or constant energy consumers. In this regard, the proposed work has considered and expanded the same idea from analytical as well as implementation point of view to multiple EV charging regions and respective loads. We present a novel mechanism to calculate EV charging prices using individualized energy consumption patterns of EVs in each region. In this regard, all EV regions/stations receive a dynamic price signal which is non-discriminatory in nature. The dynamic price signals are specifically designed to mitigate the impact of discriminatory prices on end user's cost. Furthermore, the other objectives of these non-discriminatory prices are to lower energy cost and rebound peaks without affecting utility objective (i.e., net revenue). Initially, a new mathematical model is presented to calculate charging prices based on real time load demand and market dynamics. Then relatively a well behaved functional form of the optimization problem is formulated and the cost minimization objective function is solved by using genetic algorithm (GA). The optimization program successfully converges to give global optimum solution validating the effectiveness of proposed mechanism. Finally, the analytical and simulation results are conducted to show the achievements of our proposed work in terms of fair cost distribution with high user satisfaction. It is also proved that in both mechanisms, the utility's revenue remains unaffected.

INDEX TERMS Demand response, electric vehicles, charging prices, constraint optimization, homogeneous price policies.

NOMENCLATURE

$i \in n$	index for users
$t \in T$	index for time
x	number of sub-partitioned users
$\mathcal{U}$	index for EV charging stations/users
μ	EV ON/OFF state
t_s	start time of EV load
t_f	finish time of EV load
t_a	arrival time of EV load
t_s^*	scheduling horizon of EV load
P_x^d	power demand for x user
$\overline{P_i^d}$	max. power demand for i^{th} user
$\underline{P_i^d}$	min. power demand for i^{th} user
$\mathcal{P}^x$	total power demand of x users
$\hat{r}$	global price for purchasing electricity
$\tilde{r}$	proposed price for purchasing electricity
$\hat{C}$	total EV charging cost using $\hat{r}$ pricing policy
$\tilde{C}$	total EV charging cost using $\tilde{r}$ pricing policy

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

vc_s	vehicle charging station
δ	control parameter to calculate new price
$\ell_{i,t}$	load demand of i^{th} user for time t
$d_{i,t}$	delay experienced by i^{th} user over time t
$\overline{d_{i,t}}$	maximum delay experienced by i^{th} user over time t
$d_{i,t_{avg}}$	average delay experienced by i^{th} user over time t
$\omega_{i,t}$	actual delay experienced by i^{th} user over time t
$\tau_{i,t}$	operating time of EV load i over time t
$\sigma_{i,t}$	pre-service time delay of EV load
c_i^r	required charging intervals of i^{th} user
c_i^{sch}	scheduled charging intervals of i^{th} user
t^{sch}	scheduled time for EV charging
$f(t_a, \tau_i)$	a function used if $\ell_{i,t}$ can be served within service time [0,1]
$\mathbf{v_i}, \mathbf{s_i}$	auxiliary vectors
$\kappa_{i,t}$	charging/discharging rate of i^{th} user over time t
$soc_{i,t}$	soc of i^{th} user over time t
$soc_{i,t-1}$	soc of i^{th} user over time $t-1$
$\overline{soc_i}$	upper limit on soc of i^{th} user
$\underline{soc_i}$	lower limit on soc of i^{th} user
$soc_{i,t}^d$	soc demand of i^{th} user over time t

I. INTRODUCTION

In recent years, a large scale adaptation of EVs will affect two cyber-physical networks: power and transportation [1]. Numerous studies have already been presented to discuss these infrastructure systems regarding their operational point of view. It is found that these network systems are coupled as they provide energy resources with reduced CO_2 emissions along with green environment. However, in this work, we argue that integration of EVs in residential and commercial premises will couple both power and transportation networks. Thus, without considering their interconnection and assuming that charging and location of EVs follow an independent process that does not get affected by electricity charging prices may create instabilities in power systems due to unfair price distribution [2]–[4]. Furthermore, customers may also be discouraged to participate in market based DR programs without providing monetary or other incentives. In addition, the increased charging cycles will pose a serious challenge that what type of pricing model can be employed given the possibility of massive power extraction. So, to resolve this issue, there needs to design an EV charging pricing mechanism in such a way to facilitate end users and energy retailers, simultaneously. Hence, this work proposed a new distributed scheduling and pricing mechanism for EV charging stations at different regions.

To solve these issues, this work presents a distributed pricing model for EV charging load management. The proposed pricing policy is designed to impartially charge the EVs in such a way that electricity prices are unbiased. To further analyze the economic benefits of the proposed mechanism, we first develop a mathematical model of constructing EV charging prices. Then constraint optimization problem has been formulated and heuristic solution is obtained to minimize the EV cost. For validation, we compare two scenarios: (1) the EVs follow FCFS policy without power and delay limits, (2) optimized vehicles' charging patterns considering power and delay limits. The extensive simulation results indicate that the proposed pricing model significantly reduces the charging cost while facilitates the respective customers by providing them customized price policies.

A. MOTIVATION

Analysis in [5] gives the results of total EVs registration data analysis from January 2013 to October 2016, obtained from New York State (NYS) department of motor vehicles over the given time. It can be observed that in year 2015, there were in total 1950 registered EVs in NYS. While in year 2016, this figure increased 49.335% and total 2912 vehicles registered. It is therefore concluded that the penetration of vehicles is expected to increase in coming years imposing serious effects on electric transmission and distribution systems, if EV charging processes are not managed properly [6]. On the other hand, EV penetration in residential premises may increase the electricity demand during evening hours known as "duck curve" may pose serious challenges regarding high peak to average demand ratio for the energy market. Many researchers have been working to manage the load demand and duck curve challenges by encouraging the customers to shift their loads through various pricing and incentive based schemes [7]. This motivated us to further investigate the EV charging prices through adoptable strategies and develop a dynamic pricing model for temporal load shifting during high peak hours. It is also important to mentor here that in a consumer oriented electricity market, utilities and energy retailers cannot directly deny providing services to EV owners and residential customers, even when a power grid has stability problem. In this situation, the consumption behaviour can be greatly influenced by properly adjusting the electricity consumption prices. Therefore, a price calculation can be used as a significant tool in EV network. Therefore, a dynamic pricing has been an active area of research, where researchers has already made some contributions [8]–[10]. However, non of the developed solutions has addressed the challenge of customized price distribution.

In summary, the major contributions of the paper are discussed as follows:

- Firstly, based on EV arrival and power consumption models, scheduling has been performed in terms of cost reduction and social welfare maximisation.[1] Day-ahead electricity pricing policy, FCFS mechanism and GA are used to solve constraint optimization problem with the primary objective to facilitate end users.
- Secondly, we propose a distributed pricing mechanism based on; aggregated load demand, day-ahead pricing, individualised load demand profiles and load demand

[1] Social welfare maximisation in terms of scheduling delay is considered in this work.

patterns of EVs. Then a constraint optimization problem has been formulated and a heuristic solution is obtained indicating that EV charging price is different for all charging stations.

- Thirdly, to analyze the proposed pricing model, analytical results of the mathematical model are obtained which are further validated via extensive simulations using a real time data set of a moderate size. Furthermore, the obtained results are compared with traditional pricing which is usually calculated on the basis of aggregated load demand.
- Finally, it is also proved that optimization problem is formulated in such a way that GA efficiently solved the problem to obtained a closed form solution without constraint violation. Furthermore, to avoid premature convergence, the local best solution in each iteration is compared with previously obtained best solution. The results presented in table 2 reflect the significance of proposed mechanism in terms of fair price distribution among all charging stations.

It should also be noted that the proposed pricing model has a direct impact on end users, charging station owners and energy retailers as well. In this work, along with proposed mechanism, we also consider a grid stability issue caused by an increased charging load demand during peak hours, which is a major challenge. We assume that since the energy retailers will enjoy the maximum benefits in terms of grid stability, they will provide the incentives to the users in terms of adjustment in selling electricity to further promote the proposed pricing model.

The rest of the paper is organized as follows: section II provides related work, section III and IV discuss the system model and mathematical problem formulation of the proposed mechanism, simulation methodology and results have been discussed in sections VI and VII, respectively. Subsequently, the conclusion is given in section VIII.

II. BACKGROUND LITERATURE

In literature, various mechanisms have been presented to provide the optimized charging schedules of EV in response to DR programs [11]–[15]. Where, most of the techniques have been designed with a twofold objective: (i) to reduce the electricity cost of potential users while adopting both vehicle to grid (V2G) and grid to vehicle (G2V) integration options. The primary objective is to smoothen the power demand and supply through intelligent optimization mechanisms in response to dynamic electricity prices [16], [17]. In [18], authors have proposed a vehicle charging mechanism using DR programs by taking into consideration random charging patterns of EVs. A load shaping problem with the effective utilization of DR programs in a distributed and decentralized framework has been discussed in [19]. Another study proposes an efficient power management system where authors have introduced a mechanism which decides when to discharge their EVs [20]. Furthermore, to mitigate voltage and power demand imbalances caused due to massive power extraction and photo-voltaic integration, algorithms decide when to start V2G operation without compromising on user comfort. To facilitate the adaptation of EV use, real time interaction between load aggregators and EV parking lot owners has been established through intelligent power management mechanisms [21]. On the other hand, to further facilitate the EV customers, predicted electricity prices have been used for charging purposes [22]. A Bayesian neural network and linear programming technique have been used for predicting electricity demand and decision making, respectively. It is also estimated that up-to 15% saving can be achieved by employing this technique. Another EV charging mechanism by taking into consideration the aggregated charging load on a specific bus has been proposed in [23]. This mechanism has twofold objective: (i) minimizing the feeder losses due to uneven load drawn, and (ii) facilitating maximum number of EVs for simultaneous charging. These objectives have been achieved through proper estimation of total number of EVs which is modelled as a Poisson arrival process, as it is understood that the utility's profit is directly linked with the high sale of electricity. Consequently, this may create rebound peaks if fleet charging prices are used, where customers wish to charge EVs when charging prices are lower. A linear programming model to minimize the customer's charging expense and to maximize the aggregator's profit has been proposed in [24]. To facilitate both customers and utilities without violating their objectives, a novel DR mechanism has been proposed [23]. This mechanism provides benefits to customers with optimal charging patterns in accordance with user demand. Meanwhile, the power system can be made stable through imposing maximum power consumption limits. Another work has been proposed to devise a profit-optimal pricing mechanism facilitating both EV charging customers, without violating the aggregator's objectives [25]. To achieve this objective, EV's characteristics and mobility patterns have also been considered. For validation, the mechanism is implemented and tested on a set of EVs having moderated size. To minimize the EVs charging along with peak reduction, a hierarchical control mechanism across multiple aggregator has been proposed [26]. Distributed system operators first solve the charging curve at their premises and then heuristic algorithm is used to allocate optimal power to EVs. In [27], [28], mathematical optimization models have been solved by using mixed integer linear programming and fuzzy linear programming to maximize the aggregator's profit. EV charging problem to maximize the parking lot owner's profit has been solved by using linear programming technique [29]. This problem, however, can also be solved by using quadratic programming technique. Similarly, a quadratic programming technique is used to minimize the EV charging prices [30], [31]. Another work reported in [32] discusses the interdependence and collaboration between independent power and transportation systems operators that can lead towards cost efficient and socially optimal patterns of EV charging. Furthermore, reserve capacity requirement of operating the grid is also analyzed in the absence of these

TABLE 1. Comparison of proposed work against various related works.

Reference	Objective	Optimization Technique	Pricing Mechanism	Operator/Agent	Limitations
[12]	Min. the impact of EV charging	Scheduling Algorithm	RTP	DSO	Reschedules can cause user discomfort which is implicitly discussed
[13]	Max. user comfort	Scheduling Algorithm	RTP	Private/Residential EV owners	User comfort is compromised, EV impact on DR is implicitly analyzed
[18]	Min. peak load demand	LP	DAP	Retailer/Aggregator	Load shaping via EV scheduling can disturb user comfort
[19]	Optimize EV charging schedules	Gradient Ascent, Incremental Stochastic Gradient	MPS	Aggregator	User objectives are not fully optimized
[20]	Min. Voltage Unbalance	Decision-making Algorithm	RTP	EV Distributors/EV Owners	User comfort could be disturbed
[21]	Max. EV Penetration	MILP	RTP	Aggregator & EV Owners	Trade-off between cost reduction and comfort maximization objective
[22]	Min. EV battery charging cost	Batch Reinforcement Learning, Bayesian Neural Network, LP	DAP & Predicted Prices	Residential EV Owners	Load variation can disturb customer objective, Less attentions are given to utility objectives
[23]	Max. Charging Schedules	Artificial Neural Network	TOU	EV Parking Stations	Customer and utility objectives are not jointly optimized
[24]	Min. charging cost, Max, aggregator's profit	LP	SDA, D-RTP	EV owner, Aggregator	Trade-off between aggregator and customer objective
[26]	Min. electricity cost, Min. peak load	LP	DAP	DSO	Load variation may disturb aggregator's profit
[27]	Max. utility/aggregator's revenue	MILP	RTP	Aggregator	Aggregators objective is only focussed
[28]	Max. utility/aggregator's revenue	FLP	RTP	Aggregator	EVs charging schedules and consumption limits need to be considered
[29]	Max. charging lot profit	LP+FCFS & EDF	TSP	EV parking lot owner	High peaks due to charging overload
[30]	Min. charging cost	QP	TSP	EV owners	Complexity analysis, User comfort due to EV schedules, Impact of high energy demand on market price basis
[31]	Min. load variation	QP	DAP	Grid operator	EVs users, Impact of DR and charging prices on end user cost is missing
[45]	Max efficient power dispatch	Particle Swarm Optimization, Distribution Algorithm	RTP	Municipal Parking Station	Aggregator's revenue is utility dependent
[46], [47]	Max. SOC of EV	Swarm Intelligence	RTP	Parking lot owner	Non of small consumers are charged on aggregated DR basis
Proposed	Min. charging cost and average delay of PEV	Swarm Intelligence	RTP	EV parking stations	This scheme is only valid for EVs operated under DSO

two infrastructures. Then a control strategy under a static operating conditions is established to facilitate individual EV owners in terms of reduce charging cost and shortest route patterns. The initial work [33] of [32] gives general model of ''energy-aware shortest path problem'' and an extended transportation graph. In [34], an agent based distributed holistic framework is proposed which used consensus based innovation strategy to control optimal charging of EVs. The underlying objective is to improve operational performance of such type of cyber-physical systems with less information and communication exchanged using internet of things (IoTs) lens. Distributed solution is comparatively more efficient than centralized solution. However, it required advanced communication infrastructure and computing resources. Although, this work is interesting in its kind, however, customers are not provided incentives in the form of reduced charing or fair charging pricing, which may discourage them participating in market based DR programs. In this work [35], to optimize the utilization of virtual power plant involving dynamic energy resources, a two-layer approach considering safety constraint is presented. The upper layer is dedicated to maximize benefits of virtual power plants, while the lower layer is responsible for managing the charging demand through optimal scheduling. The effectiveness of the layered architecture is shown via IEEE 30 bus system test case with the integration of wind source. Table 1 gives a brief summary of relevant state of the art work.

III. SYSTEM MODEL

In this work, we consider a standard IEEE 30 bus power system topology and a multi-model transportation system topology as a test case as shown in Fig. 1, [36], [37]. The total geographical area is further divided into four sub-regions. While in each sub-region, we assume six EV charging stations $\mathcal{U} \in vc_{s_1}, vc_{s_2}, vc_{s_3}, \ldots, vc_{s_n}$ fulfilling the charging load demand from DSO [39]. A centralized charging management unit (CMU) is responsible for all types of decision making and communication services which are assumed to be provided by advanced metering infrastructure (AMI) Fig. 3. Furthermore, there is also a possibility to

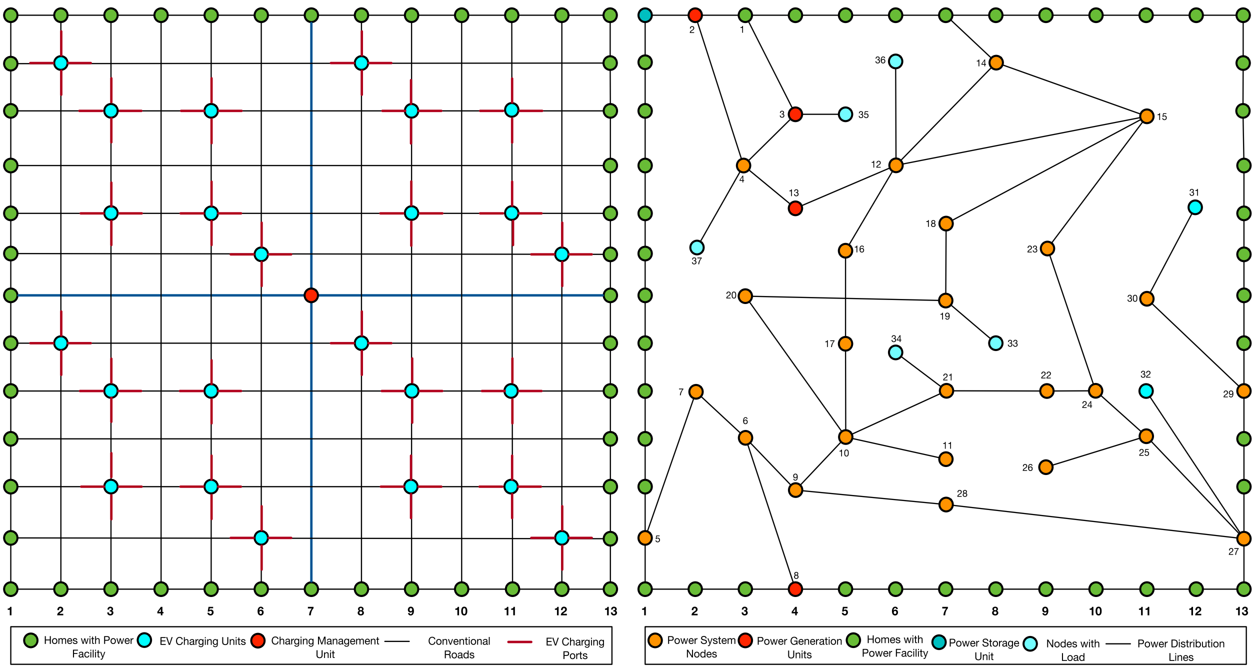


FIGURE 1. Conceptual diagram of considered system model describing degree of freedom of transportation and power grid related operands: (left) Topology of symmetrica, grid connected EV charging management system, (right) Topology of symmetrica, IEEE 30 bus system system.

integrate on-site renewable energy resources along with EVs as a backup source, whenever it is required and profitable for users. It can either maximize end user's profit or reduce total electricity expense. However, the proposed work only considers the G2V option, where fair price distribution is a primary objective. In order to achieve this objective, various electricity pricing schemes can be considered and utilized (as per given requirements). The proposed work uses RTP which is obtained from utility server.

A. EV ARRIVAL AND DELAY MODEL

It is assumed that each EV charging user has different QoS requirements depending on his preferences such as; arrival time t_a, service time t_s, and finish time t_f of driving tasks arrived arbitrarily over discrete and finite time intervals $t \in \{1, 2, 3, \ldots, T\}$. It is also assumed that arrival and departure of EVs are modelled as random variable using *Poisson* process model, with variable rate of arrival and service time, depending on user requirements (Fig. 2). Let $t_a \in \{1, 2, 3, \ldots, T\}$ be the arrival time of any EV with random and arbitrarily dynamics such that; ℓ_t is the load demand, τ_t is the length of operation duration, and d_t is the maximum allowable duration before the service time. Assume that t_s is the actual service time of any EV, which is arrived at t_a time. So, the following constraints are associated:

$$t^*_{s_{i,t}} = T - \tau_{i,t} \tag{1}$$

$$\omega_{i,t} = t_{f_{i,t}} - \tau_{i,t} + \sigma_{i,t} \tag{2}$$

In (1) and (2), QoS requirements in terms of EV's waiting time are presented. Particularly, (1) shows the condition when

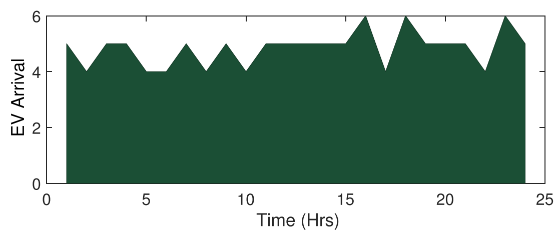


FIGURE 2. EV arrival rate over the given time.

EV users do not concern with social welfare (user comfort) objective and their scheduling horizon remains constant. Its mean, the EV charging schedules can be planned between $t_a - T$ time interval and (2) considers the pre-service time delay $\sigma_{i,t}$. We define $\omega_{i,t} \triangleq t_s - t_a$ as pre-scheduling time delay experienced by EV user. We also define the average waiting time of EV users in (3), and impose a constraint in (4) as follows:

$$d_{i,t_{avg}} = \frac{1}{T}\Big\{\sum_{t \in T} d_{i,t}\Big\} \tag{3}$$

$$0 \leq d_{i,t_{avg}} \leq \overline{d_{i,t}} \tag{4}$$

B. POWER CONSUMPTION MODEL

If all the EV charging users are given in a single set $\mathcal{U}$ and the power consumed by an i_{th} user over time t is represented by P_i, which is given as:

$$P_{i,t} = \Big\{\sum_{t \in T} \sum_{i \in |\mathcal{U}|} [f(t_a, \tau_i).\ell_{i,t}] \times \mu_{i,t}\Big\} \tag{5}$$

$$\text{subject to: } 0 \leq d_{i,t} \leq \overline{d_{i,t}}, \quad \forall t \in \mathbb{Z}^+ \tag{6}$$
$$0 \leq \tau_{i,t} \leq T, \quad \forall t \in \mathbb{Z}^+ \tag{7}$$
$$\ell_{g,t} = \Big\{ \sum_{t \in T} \sum_{i \in |\mathcal{U}|} [f(t_a, \tau_i).\ell_{i,t}] \times \mu_{i,t}(\omega_{i,t}) \Big\} \tag{8}$$
$$\mu_{i,t} = [0, 1] \quad \forall i \in |\mathcal{U}|, \quad t \in \mathbb{Z}^+ \tag{9}$$

where, $\ell_{i,t}$ in (5) denotes the energy demand of i^{th} component of EV over time t for $i = |\mathcal{U}|$. In (5), $\mu_{i,t} \triangleq \{1 : if\ \ell_{i,t} > 0 : 0\ otherwise\}$. We also assume that each EV charging station has to provide services to users which arrive over the time slot with spatial uncertainty and temporal variability. Each user has certain amount of load intensity for a specific duration $\ell_{i,t}$. We assume that the expected delay experienced by $\ell_{i,t}$ is denoted by (6). Where, (7) denotes operating interval of any EV load. Thus, $[t, t+\ell_t]$ and $[t+\overline{d_t}, t+\ell_t+\overline{d_t}]$ are the earliest and latest serving time intervals of $P_{i,t}$, respectively. While each EV arrived at time t is scheduled to serve if $t > d_\tau$, the total amount of energy demand must be equal to the energy supplied from the grid, which is depicted in (8).

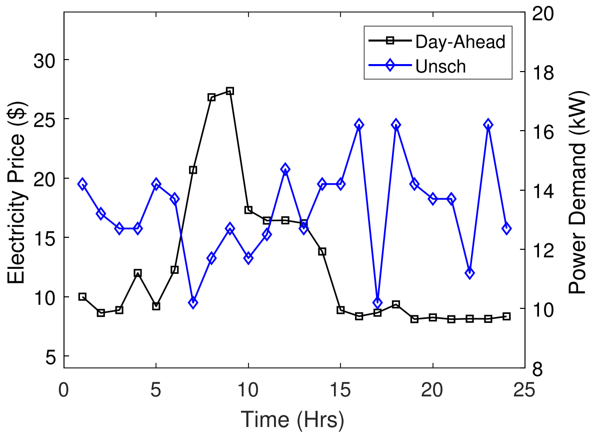


FIGURE 3. Day-ahead RTP signal and total power demand of EV charging over given time period.

C. ELECTRICITY PRICING MODELS

This paper proposes a novel mechanism to devise non-discriminatory price policies for EV charging customers. Where, instead of using the global pricing[2] $\hat{r}$ for all consumers, the "individualized prices" depending on load consumption patterns of all users have been calculated (Fig. 3). The novel aspect lies in the concept that these prices do not have any affect e be price profiles of other users, operated under the same DSO/utility[3]. Moreover, these prices have been designed such as to maximize the benefits of end users. Initially, this study considers different users/regions purchasing or selling the power. Specifically, three different vehicle charging regions; vc_{R_1}, vc_{R_2} and vc_{R_3} are considered as a test case. Whereas, each charging region contains 6 EV charging lots with infinite queuing capacity. However, before discussing mathematical models, we first discuss traditional and proposed pricing models in the following subsections.

1) DAY-AHEAD PRICING MODEL

The day-ahead pricing model can also be known as traditional pricing model is based on RTP or TOU pricing scheme, where all users/EV-stations[4], regardless of their type or power consumption, are priced with a constant rate $\hat{r}$. Generally, these prices are obtained from market retailer, which are subject to aggregated demand. Based on the energy consumption model presented in section III-B, the energy consumption cost using market price signal over time t is given as:

$$\hat{C} = \Big\{ \sum_{t \in T} \sum_{i \in |\mathcal{U}|} \tau(v_{i,t} - s_{i,t})(P_{i,t} \times \hat{r}_t) \Big\}. \tag{10}$$

Here, the parameter $(P_{i,t} \times \hat{r}_t)$ represents cost of energy at each time step, τ represents duration of each time step in hours. Variables $v_{i,t}$ and $s_{i,t}$ are auxiliary vectors $\mathbf{v_i}$ and $\mathbf{s_i}$ such that $\{v_{i,t} - s_{i,t} \triangleq \varkappa_{i,t}\}$. The variable $\varkappa_{i,t}$ represents charging or discharging rate of each connected vehicle i. These auxiliary variables lie within sets $\mathbf{V_i}$ and $\mathbf{S_i}$. Where, in (10), $\hat{r}_t$ denotes the pricing signal obtained from a day-ahead electricity pricing market, which is constructed on the basis of aggregated load demand. In literature, usually these pricing signals are being widely used to schedule the EV charging loads by assuming that there is not upper bound on energy consumption. Then by assuming that $\hat{r}$ is the only pricing signal used to provide the electricity tariff information to end users, the objective is to minimize the total charging cost subject to respective constraints.

The (10) provides the basic mechanism for the calculation of power consumption cost in response to time varying electricity prices [44]. Although this mechanism is being widely used for cost calculation. However, we have explored the literature and identified that this mechanism is infeasible when power consumption trends of various users have large variations. For example, we have $i \in n$ users consuming power at variable rate over the given course of time, whereas $\sum_{n=1}^{n} i(n-1)$ users consume power at a constant rate. As a response, the utility or retailers calculate the hourly prices on aggregated power consumption basis (i.e., Eq. 10) rather than individualized basis. Consequently, the users consuming power at a constant rate get affected as they are receiving the same hourly price irrespective to their consumption level. So, we have considered this problem and devise a mechanism which calculates the prices in accordance with individualized power consumption trends of EVs. The following section provides the details of the proposed pricing mechanism.

[2]We can refer RTP as a global pricing policy, as these prices are calculated on aggregated power consumption basis.

[3]The proposed work assumes that all charging regions or stations have been operated under the same DSO

[4]In this work, EV charging users and stations can be used synonymously.

2) PROPOSED DISTRIBUTED PRICING MODEL

Basically, the EV charging load consumed at residential premises is comparatively lower than the commercial users and parking lot users. Hence, it is unfair to charge all the users with a constant price i.e., ($\hat{r}$). To overcome this issue, the proposed scheme provides a mechanism to set a separate price signal for a single category of users or parking lot.

a: PROBLEM MODIFICATION

Let the set $\mathcal{U}$ is partitioned into distinct sets corresponding to the types of users, i.e., $[\mathcal{U}_{vc_{r_1}}, \mathcal{U}_{vc_{r_1}}, \ldots, \mathcal{U}_{vc_{r_x}}]$. The total power demand can be written as:

$$\mathcal{P}^x = \Big\{ \sum_{t\in T} \sum_{i\in|\mathcal{U}_x|} [f(t_a, \tau_i).\ell^x_{i,t}] \times \mu_{i,t} \Big\}, \tag{11}$$

where, $x \in [\mathcal{U}_{vc_{r_1}}, \mathcal{U}_{vc_{r_1}}, \ldots, \mathcal{U}_{vc_{r_x}}]$, and the total consumed power can be denoted by $\mathcal{P}^x$. In Eq. 12, we consider same pricing policy for all EV charging users and calculate the total electricity bill as:

$$\hat{C} = \Big\{ \sum_{t\in T} \sum_{i\in|\mathcal{U}_x|} \tau \varkappa_{i,t}(\mathcal{P}^x_{i,t} \times \hat{r}_t) \Big\}. \tag{12}$$

Note that, so far, it was assumed that utility has rights to calculate the relevant pricing considering the total power consumption. In the proposed work, we consider the power consumption based pricing schemes where the rate of each unit is proportional to the total number of units consumed by each user; it is modelled so that the total revenue is not decreased. We first discuss this model on charging regions level. For this purpose, we need to calculate the total amount of power consumed by the charging regions. The control parameter δ calculates the actual price to be assigned to each EV in regard with the consumption trends of other EVs. The value of $\delta_{i,t}$ for i users over time t is calculated as:

$$\delta_{i,t} = (\mathcal{U}^{-1})^2 \times ((f(t_a, \tau_i)\ell^x_{i,t}) \times \mu_{i,t}) \times \hat{r}, \ \forall t, i \in \mathcal{U}_x, \tag{13}$$

where, $\mathcal{U} = \sum_{i=1}^{|\mathcal{U}_x|}(P_i)$ and $||x||$ represents the Euclidean norm of the vector x. Soon after finding the relative charging prices for all EVs, customized price for each EV can be calculated using $\tilde{r} = P_{i,t} \times \delta_{i,t}$.

$$\tilde{r} = \Big\{ \sum_{t\in T} \sum_{i\in|\mathcal{U}_x|} P_{i,t} \times \delta_{i,t} \Big\}, \tag{14}$$

where, the vectorized form of the above equation is denoted as:

$$\begin{bmatrix} \tilde{r}^{t_1}_{x_1} \\ \tilde{r}^{t_2}_{x_2} \\ \tilde{r}^{t_3}_{x_3} \\ \vdots \\ \tilde{r}^{T}_{x_n} \end{bmatrix} = \begin{bmatrix} \delta^{t_1}_{x_1} \\ \delta^{t_2}_{x_1} \\ \delta^{t_3}_{x_1} \\ \vdots \\ \delta^{T}_{x_n} \end{bmatrix} \times \begin{bmatrix} \mathcal{P}^{t_1}_{x_1} & \mathcal{P}^{t_2}_{x_1} & \mathcal{P}^{t_3}_{x_1} & \cdots & \mathcal{P}^{T}_{x_1} \\ \mathcal{P}^{t_1}_{x_2} & \mathcal{P}^{t_2}_{x_2} & \mathcal{P}^{t_3}_{x_2} & \cdots & \mathcal{P}^{T}_{x_2} \\ \mathcal{P}^{t_1}_{x_3} & \mathcal{P}^{t_2}_{x_3} & \mathcal{P}^{t_3}_{x_3} & \cdots & \mathcal{P}^{T}_{x_3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathcal{P}^{t_1}_{x_n} & \mathcal{P}^{t_2}_{x_n} & \mathcal{P}^{t_3}_{x_n} & \cdots & \mathcal{P}^{T}_{x_n} \end{bmatrix} \tag{15}$$

where, $\tilde{r}$ denotes new price signal which is assigned to each user based on the consumed power. It is worth noting here that $\delta_{i,t}$ has been calculated by using $\hat{r}$ and power drawn by all stations and for each EV charging user, the value of $\tilde{r}$ will be different. In a result, total electricity bill $\tilde{C}$ incurred by all stations using proposed mechanism can be calculated as:

$$\tilde{C} = \Big\{ \sum_{t\in T} \sum_{i\in|\mathcal{U}_x|} \tau \varkappa_{i,t}(P_{i,t} \times \delta_{i,t} \times \mathcal{P}^x_{i,t}) \Big\}. \tag{16}$$

Now, (16) ensures that total cost/revenue of the utility remains constant when compared with $\hat{r}$. Thus, the EV charging bill can be calculated on the bases of traditional and proposed policies using (10) and (12).

b: CHARGING AND SOC CONSTRAINTS

It is assumed that EV chargers are able to handle two-way power flow and they have limited consumption or injection rates that must be considered in the optimization problem. These charging rate is described as [38]:

$$\underline{P^d_i} \leq \varkappa_{i,t} \leq \overline{P^d_i}, \quad \forall i, t \tag{17}$$

where, $\underline{P^d_i}$ and $\overline{P^d_i}$ represent power limits of EV chargers. In (17), $\varkappa_{i,t}$ represents charging/discharging rate of i^{th} user over given time. If $\varkappa_{i,t}$ is expressed as difference of two variables $v_{i,t}$ and $s_{i,t}$, as shown in (10), then the (17) can be modified as:

$$0 \leq w_{i,t} \leq \overline{P^d_i} \quad \forall i, t \tag{18}$$

$$0 \leq s_{i,t} \leq \overline{P^d_i}, \quad \forall i, t \tag{19}$$

where, $v_{i,t}$ and $s_{i,t}$ are elements of auxiliary vectors $\mathbf{v_i}$ and $\mathbf{s_i}$. The (18) is only valid just before the departure time of EV. Similarly, the battery state of any EV, at the end of time t can be modelled as:

$$soc_{i,t} = soc_{i,t-1} + \tau \sum_{t\in T} \varkappa_{i,t}, \quad \forall i, t \tag{20}$$

where, $soc_{i,t-1}$ represents charging state in previous hour. In order to prolong EV battery life time, it is required to avoid deep discharging. For this purpose, we implement limits on charging such as:

$$\underline{soc_i} \leq soc_{i,t} \leq \overline{soc_i}, \quad \forall i, t \tag{21}$$

where, $\underline{soc_i}$ and $\overline{soc_i}$ represent lower and upper limits on EV battery charging states. The charging limits based on actual load demand over the given time interval is given as:

$$\underline{soc_i} \leq soc_{i,t} + \tau \sum_{t\in T} \varkappa_{i,t} \leq \overline{soc_i}, \quad \forall i, t \tag{22}$$

The expressions (20),(28),(27) demonstrate the generalized form of limits, while it is required to meet the minimum lowest charging requirement. Thus, it is more restrictive to impose desired $soc^d_{i,t}$ limit, based on demand requirement. This limit is expressed as:

$$(soc_{i,t} + \tau \sum_{t\in T} \varkappa_{i,t}) - soc^d_{i,t} = 0, \quad \forall i, t \tag{23}$$

Finally, (29) gives the expression to meet the required SOC requirements of all EVs, currently participating in charging process.

D. PRICE HOMOGENEITY

Intuitively, in order to have parking lot owners and other EV users agreeing on paying bills in accordance with proposed model (i.e., homogeneous pricing policies), it is required that such prices must be non-homogeneous. In another words, the newly calculated prices must be based on the actual power consumption of EVs parking lot owners, regardless to the $\tilde{C}$ which are calculated on aggregated power consumption basis. This is also necessary for EV users, parking lot owners as well as electricity retailers and distributors to keep their objectives (i.e., net profit/revenue that should not be reduced due to discriminatory prices). Otherwise, discriminatory prices would ultimately reduce the total number of participants adopting such pricing schemes and DR programs, causing reduction in utility's revenue. However, in our context, we can informally say that the prices are non-homogeneous if all the users have same opportunity to pay their bills when such prices have been calculated in relation with others consumption levels. Moreover, the proposed mechanism for price calculations is also feasible when EV users and parking lot owners are not willing to participate in DR and load management programs. In this case, prices are calculated on the basis of power consumption levels. Formally, we can define the tariff as; $\tilde{r} = (P_i, \mathcal{P}_x, \hat{r}, \delta_i)$. Where, δ_i gives the fraction of power used, based on which the non-discriminatory prices are calculated. The important point to note here is the value of δ_i which decides the amount of bill by taking into consideration the power consumption of all other users operating under same DSO. For this purpose, real time load consumption data is required, which can be collected from [39]. Since, $\hat{r}$ is fixed for all types of users, however, $\tilde{r}$ for all vc_{R_n} are dynamic non-discriminatory prices.

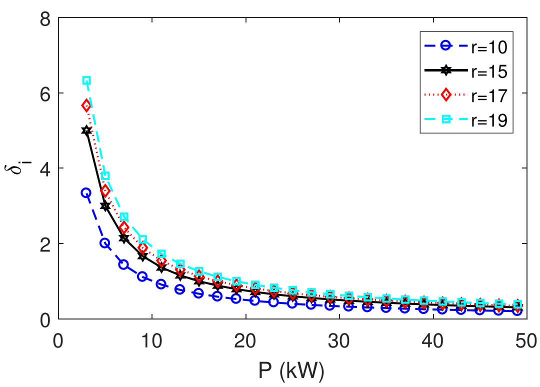


FIGURE 4. Relationship between P and δ_i as a function of $\hat{r}$ over the given time. Day-ahead RTP is used in our case.

Generally, the proposed price policies depend on δ_i (Eq. 13). Whereas, the δ_i further depends on two factors, i.e., u_i and $\hat{r}$. To show the dependence of δ_i on P and $\hat{r}$, we provide numerical results as shown in Fig. 4. The figure shows relationship between δ_i and P_i, while, the value of $\hat{r}$ is varying over given time period. From figure, it is obvious that value of δ_i decreases if we increase P_i and vice versa. Intuitively, if any vehicle or parking lot requires more or less power, the δ_i will decide the charging cost with respect to load consumed (Eq. 13).

Lemma 1: Let $\delta_{i,t} = (\mathcal{U}^{-1})^2 \times ((f(t_a, \tau_i)\ell^x_{i,t}) \times \mu_{i,t}) \times \hat{r}$, denotes the pricing policies for for EV stations in time T, and $\hat{C}$ (Eq. 24) is the resultant energy consumption cost for all charging stations. Let suppose, if total EV charging cost is from residential viewpoint $(P_{i,t} \times \mu_{i,t} \times \hat{r}_t)$ is equal to expected cost of utility $\delta_{i,t} \times \mathcal{P}_{i,t}$ in such a way that condition $\delta_{i,t} \times \mathcal{P}_{i,t} = P_{i,t} \times \mu_{i,t} \times \hat{r}_t$ is satisfied. Then it is proved that price policies obtained from proposed algorithm are homogeneous. For proof, see appendix.

IV. PROBLEM FORMULATION

Based on load demand and user requirements, this work considers two cases: (i) it is assumed that charging stations have infinite queue capacity and charging cost is calculated using a day-ahead pricing model, (ii) charging stations have finite queue capacity, hence some delay could be occurred. In addition, users intend to reduce their charging cost and are willing to participate load management programs. Initially, the ***P1*** is solved and total cost is obtained using a day-ahead pricing policy. Then, this cost is used as an input to solve ***P2*** using proposed pricing policy. For validation, the results of both cases are compared (Table 2). Each case has some assumptions, which are discussed as follows:

A. ASSUMPTIONS 1

1) EVs are charged as per schedules given by the users and there is no limit on the power consumption. It is assumed that EV charging lots are empty and any EV can get charged at any time without bearing delay.
2) For cost charging cost reduction, an optimization program is used, while the proposed mechanism is used to distribute charging prices, fairly among all EVs.
3) There is no additional cost charged to EV for consuming high power, even during peak hours.
4) Charging prices for EVs are fixed for the given interval which is; (i.e., 60 min., charging interval is considered in the proposed work).
5) EV charging prices are assumed to be varied in accordance with the aggregated amount of power in the same DSO.

Then, on the basis of aforementioned assumptions, the objective function is formulated as follows:

$$P1 = \min \left\{ \sum_{t \in T} \sum_{u \in |\mathcal{U}|} \tau \varkappa_{i,t} [P_{i,t} \times \mu_{i,t} \times \hat{r}_t] \right\} \quad (24)$$

where,

$$P^d_{i,t} = P^s_{i,t}, \;\; \underline{P^d_i} \leq P^d_{i,t} \leq \overline{P^d_i}, \; \forall T, i \in \mathcal{U}, \quad (25)$$

subject to: (1), (7), (8), (9), (17 − 23)

$$d_{i,t} \neq 0, \quad \forall t \in \mathbb{Z}^+, u \in |\mathcal{U}| \quad (26)$$

$$\sum_{t \in T} \sum_{i \in |\mathcal{U}_x|} [(P_{i,t} \times \mu_{i,t}) \times \delta_{i,t}] \times \mathcal{P}_{i,t} - \sum_{t \in T} \sum_{i \in |\mathcal{U}|} (P_{i,t} \times \mu_{i,t} \times \hat{r}_t) = 0, \quad \forall i, t \quad (27)$$

Eq. (24) denotes the cost minimization objective function, (26) denotes that EV charging load is scheduled as per user requirement without bearing any delay, (27) ensures the cost balance in both pricing mechanisms. It is understood that the aforementioned problem formulation is done with the objective of fair cost distributions (i.e., electricity prices in accordance with net power consumed) among all EV charging customers. However, there is no pre-scheduled mechanism used, which means that users can charge EVs whenever they desire. If we consider electricity market, there is always an uncertainty on power generation due to dynamic power demand, which can disturb supply-demand balance objective. In order to cope with this problem, various authors and scientists have devised load scheduling and EVs charging mechanisms in relation with consumer and utility constraints [18]–[23]. Few authors focus on EV charging schedules [30], [31], [45]–[47]. While others proposed EV charging scheduling in accordance with price based DR programs [18], [19], [21], [23]. In the later case, there is a possibility that EV charging customers can put on waiting queues due to high electricity prices in particular hours. As a consequence, the cost-saving customers may bear extra delay while receiving extra benefits in the form of reduced bill, while the other customers do not want to bear delay, even if charging prices are high. In contrast to first case, the second case has been considered in the proposed work to schedule EV charging schedules in order to reduce charging cost along with reduction in high peaks. Therefore, we have used the proposed scheduling algorithm to perform the required actions while keeping the utility and EV user's objectives. For this purpose, the following assumptions have been made:

B. ASSUMPTIONS 2

1) EVs can be charged in accordance to the optimal schedules provided by algorithm. This may create some delay in EV charging, however, there is no limit on the power consumption.
2) If the charging lots are busy in serving other vehicles, then the users can wait until to the availability of next possible time slot. Now, it depends on the situation that how much delay an EV has to bear. In the proposed work, delay factor is not considered and the focus is towards fair cost distribution among all EV users.
3) There is no limit on consuming high power even during peak hours, so there is no extra charge.
4) Charging prices for EVs are assumed to be fixed for a given interval of time. However, EV charging prices are optimally distributed among all users, which are calculated on the basis of proposed mechanism.
5) If any EV requires more charging time, then the charging prices for all respective hours would eventually depend on four factors: (i) market clearing price, (ii) aggregated power demand in a particular region, upon which market clearing prices depend (iii) total amount of power required for EV charging, and (iv) λ_i.

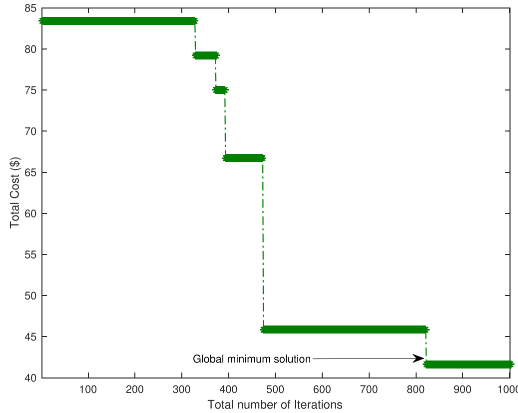


FIGURE 5. Total number of iterations of GA in achieving global minimum solution.s.

Fig. 6 elucidates the steps for calculating EV charging prices using traditional and proposed mechanisms.

Keeping in view the aforementioned considerations, the objective function can be written as follows:

$$P2 = min \left\{ \sum_{t\in T} \sum_{i\in|\mathcal{U}_x|} \tau \varkappa_{i,t}\big[(P_{i,t}\times\mu_{i,t}\times\delta_{i,t})\times\mathcal{P}_{i,t}\big] + d_{i,t_{avg}} \right\}. \tag{28}$$

subject to: $(1-9), (17-23), (26), (27)$

$$\overline{d_{i,t}} \le (t_{s_{\ell_{i,t}}} - t_{f_{\ell_{i,t}}}), \quad \forall i, t \tag{29}$$

V. PROPOSED ALGORITHM

In order to solve the optimization problem (28), heuristic based GA is used. As on/off state is involved in making load decision. Therefore, a binary version of GA is used to model EV charging states. Initially, the random arrival of EV is served using FCFS policy, without considering waiting and service time delay. Then, a day-head pricing policy is used to calculate charging cost based on extracted load. In addition, we also introduced a distributed pricing mechanism, considering multiple DSOs. For this purpose, optimized charging patterns of EVs considering pre-service and charging delay are obtained to calculate charging cost. The second problem (28) is relatively more complex and difficult to solve by using mathematical approaches [27], [28]. This is due to inherent uncertainty in EV; arrival, departure and service time in the presence of dynamic pricing and power demand. Furthermore, when dealing with classical problems, it is highly desirable to have a solution which is globally best or rather a closed form solution. In contrast, the time complexity of mathematical solutions may increase if global best solution is not found, especially, when uncertainties are there. To handle these limitations, heuristic algorithms [48]–[50] are gaining popularity due to their capability to handle uncertain and random parameters. Because, the global best solution is obtained from locally optimal solutions from the entire search space. These algorithms may also take more processing time if global optimal solution is difficult to obtain. However, at the end, there is at least closed form solution obtained. From Fig. 5, it can be seen that based on proposed model, GA converges within feasible time to give global best solution. From simulation and analytical results, it is evident that obtained solution is best in terms of fair cost distribution. To further improve this ability, the search space can be expanded, leading to higher computational time.

In proposed algorithm, before solving (28), we first solve (24) to obtain the vector containing all optimal values of EV charging users. Then, this information is used in (28) to calculate EV charging prices using proposed mechanism. To ensure whether the EV charging prices obtained from proposed mechanism are approximately equal to the total cost returned to energy retailers, the (27) is imposed which is validated once the algorithm completes one cycle.

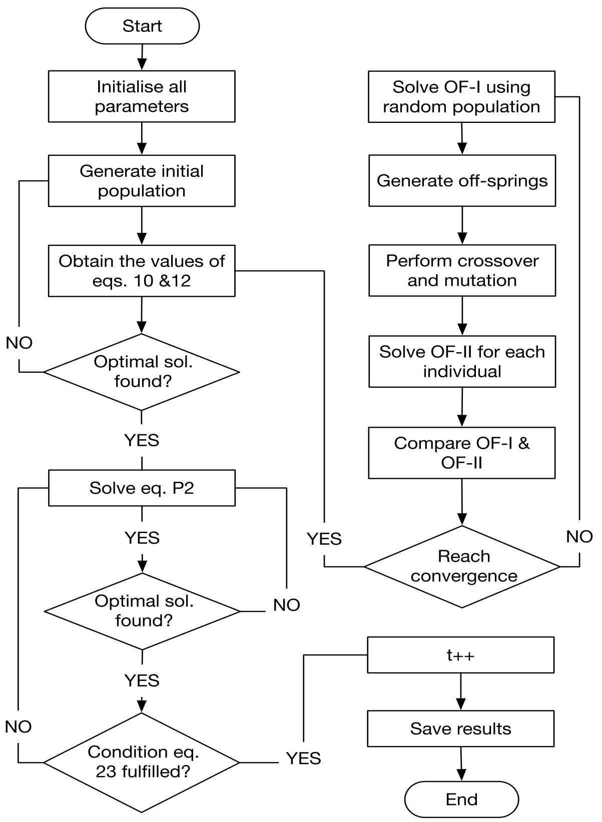


FIGURE 6. Flowchart representing the mechanism of finding distributed price policies for EV charging station.

We first solve the optimization problem *OP* (24) to get the values of $\tilde{r}$ and $\hat{C}$. So that, we can solve the *OP* in (28) to find the optimized cost of all EVs such that the total cost must be equal to the cost obtained from *OP* in (24). Eq. 28 denotes cost minimization objective function, (27) depicts that total charging cost in traditional and proposed pricing models remain same, without disturbing utility and user objectives, (29) describes the scheduling horizon of any EV arrived at charging station over user specified time instant. It means, the EV charging activity has to be performed before the start of next scheduling horizon, which is considered to be started after 24 hours. Because, the proposed test cases are performed on 24 hours equally spaced time slots. *Details of Flowchart*: Fig. 6 describes EV load management and pricing mechanism using proposed algorithm. Just like traditional pricing mechanism, we first calculate total cost in accordance with aggregated load. Then aggregated load and individual load patterns are used as input parameters to calculate separate price profile for all types of charging stations or users. To validate, whether the cost obtained from proposed mechanism, the optimization problem is solved by using GA and results are compared with traditional pricing mechanism. It is worth noting here that proposed pricing mechanism is purely based on utility function eq. (13). From Fig. 6, it can be seen that algorithm has to satisfy optimality, convergence and equality eq. (22) conditions. The results section describes and discuss the achievements of proposed mechanism.

VI. SIMULATION METHODOLOGY

The optimization problem for cost minimization has been formulated as a linear programming that aims to reduce the charging bill of EV customers. Each user can operate in any region in accordance with power demand and preferences. However, to maximize user comfort, two different modes of EV charging have been discussed in this work: (i) there is no limit on the power consumption over the given time, and (ii) EVs are provided the upper limit on extracting the power. Where in both cases, EV charging bills are calculated on the bases of individualized as well as aggregated [11], [23] power consumption profiles.

The optimization program is demonstrated on a test case of moderate size where each EV followed random arrival process [51]. This test case is selected due to two main reasons: (i) EV arrival and departure patterns reflecting realistic charging behaviors, and (ii) the total amount of power demand over the given time period provides the demand profile to effectively manage the power generation and and respective tariff. The hypothetical test case consists of three charging regions with random distribution of EV arrival. For EV charging cost, a RTP mechanism has been used in which the prices are known in advance [44]. Fig. 3 gives the relationship between power and cost.

VII. RESULTS AND DISCUSSION

Fig. 7 shows a comparison of unscheduled and scheduled load demand of EVs over given time period. It can be observed from figure that proposed scheduling mechanism reschedules charging patterns on the basis of market clearing prices and user requirements. Although the charging prices have reduced significantly, however, the user comfort is compromised. For example in Fig. 7f, the unscheduled demand request received at 10:00 shows that if scheduled, the resultant cost would be higher. This typical results originate from the fact that cost curves are independent to the EV demand profiles, leading to dynamic cost curves. Hence, a day-ahead RTP which is generally known in advance may produce unrealistic results. Similarly, Fig. 8 elucidates a comparison of unscheduled and scheduled power consumption profiles of EV over given time period. Such a demand profile depicts more exaggerated optimization condition instead of found in real life EV

TABLE 2. Comparison of power consumption cost results using traditional and proposed pricing schemes.

	Traditional Pricing Mechanism														
	Unscheduled Cost ($)							Scheduled Cost ($)							
	C_{vcs_1}	C_{vcs_2}	C_{vcs_3}	C_{vcs_4}	C_{vcs_5}	C_{vcs_6}	Total	C_{vcs_1}	C_{vcs_2}	C_{vcs_3}	C_{vcs_4}	C_{vcs_5}	C_{vcs_6}	Total	%age
vcr_1	495	684	431	539	738	799	3685	467	609	386	598	696	817	3572	3.066
vcr_2	297	456	538	754	632	266	2944	288	410	481	709	590	272	2751	6.55
vcr_3	694	342	431	539	780	799	3583	744	294	414	577	709	821	3558	0.69
	Proposed Pricing Mechanism														
	Unscheduled Cost ($)							Scheduled Cost ($)							
vcr_1	442	718	306	477	897	845	3685	423	660	279	528	830	853	3572	3.066
vcr_2	192	382	531	1001	727	112	2944	199	327	463	942	684	136	2751	6.55
vcr_3	819	180	301	468	982	833	3583	902	168	289	492	863	844	3558	0.69

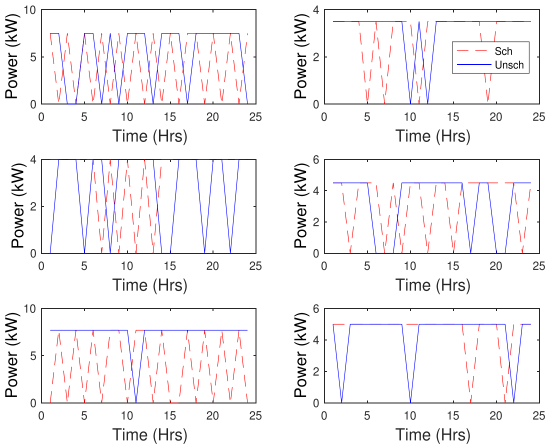


FIGURE 7. A comparison of scheduled and unscheduled vehicle scheduling and load demand pattern based on proposed pricing model, over the given time. These results are obtained for 6 charging stations in single area, as shown in Fig. 1.

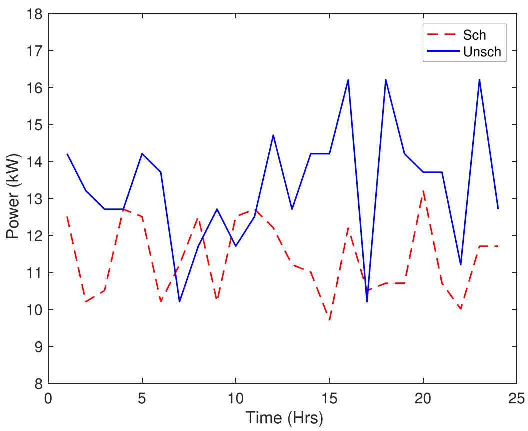
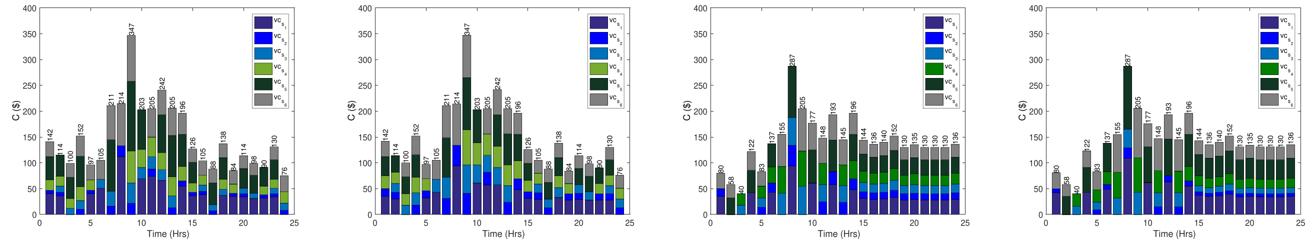


FIGURE 8. A comparison of scheduled and unscheduled vehicle load demand based on proposed pricing mechanism over the given time.

arrival demand. The scheduled demand profile is comparatively more balanced due to limit on maximum power consumption. Fig. 9 depicts the EV charging cost profiles over the given time. Such a cost profile reflects the commonly found EV charging patterns. However, the cost profiles shown in Fig. 9 shows a most exaggerated cost patterns obtained by using traditional and proposed mechanism, respectively. It is also clear from the figure that resultant hourly cost in both unscheduled and scheduled cases remains unaffected, reflecting the real time applicability of the proposed mechanism. For example in time slot-7 (Fig. 9a), the EV charging cost in unscheduled case of vc_{s_2} is more as compared to Fig. 9b. However, the total power consumption cost, i.e., 105$ in both cases remains same. This gives a clear understanding about the proposed mechanism which calculates the charging cost on the basis of net power consumption without only considering charging prices, particularly. Similar is the case with other time slots. In contrast, Fig. 9c,d gives the scheduled cost profiles of EV charging over the given time interval. In this case, the optimized EV charging schedules have been obtained and then charging cost is calculated in accordance with traditional and proposed mechanism mechanisms. It is also noticeable that comparatively more stable EV charging cost profiles have been obtained regardless to the power demand patterns and customer preferences. Dynamic cost patterns of scheduled load elucidate the fact that these cost trends are subject to the proposed mechanism. It can be further seen from the cost profiles of each charging station, clearly demonstrating the variation in EV charging cost. Furthermore, cost profiles (Figs. 9c,d) demonstrate the smooth power consumption behavior (hours 15-24) due to lower electricity tariff as shown in Fig. 3. Fig. 10 gives a brief overview of EV charging cost in response to a day-ahead and proposed models over the given time interval. Figs. 10a,b provide unscheduled and scheduled cost profiles using a day-ahead and proposed pricing models. Such a cost profiles reflect the impact of distributed pricing mechanism, which is based on dynamic load demand trends. On the other hand, RTP or TOU pricing schemes being widely used for load scheduling are unable to handle dynamical. In a response, the overall cost profiles may pose serious concerns to potential users. Similarly, to overcome such types of concerns, the proposed mechanism has the capability to not only schedule EVs for cost reduction, but also useful in constructing electricity price in such a way to maintain certain degree of fairness. It is therefore reflected from Fig. 10c,d that total cost in response to both day-ahead and proposed models remains same. While, the hourly cost of each charging station is different, which depends on load demand variation (Fig. 9, table 2). In other words, the EV charging price of each stations would be different in a particular hours, even if the market clearing



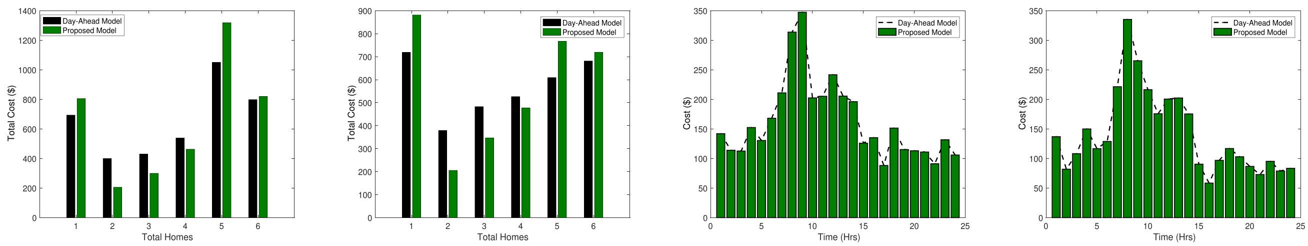
(a) EV charging cost incurred by all charging regions using traditional mechanism (unscheduled case), vc_{s_1}=vehicle charging station

(b) EV charging cost incurred by all charging regions using proposed mechanism (unscheduled case)

(c) EV charging cost incurred by all charging regions using traditional mechanism (scheduled case)

(d) EV charging cost incurred by all charging regions using prorposed mechanism (scheduled case)

FIGURE 9. Analyzing the impact of traditional and proposed mechanisms on EV charging cost in response to RTP.



(a) EV charging cost incurred by all charging regions using traditional mechanism (unscheduled case), vc_{s_1}=vehicle charging station

(b) EV charging cost incurred by all charging regions using proposed mechanism (scheduled case)

(c) EV charging cost incurred by all charging regions using traditional mechanism (unscheduled case)

(d) EV charging cost incurred by all charging regions using prorposed mechanism (scheduled case)

FIGURE 10. A comparison of a day-ahead and proposed models on EV charging cost over given time period.

price is same. Thus, the proposed model reduces the charging cost through calculating sub-prices without violating physical limits.

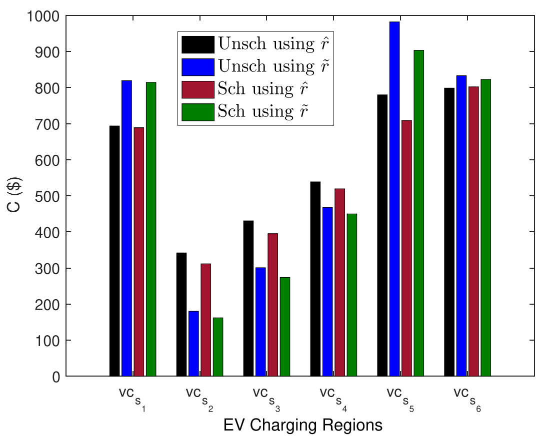


FIGURE 11. A comparison of total EV charging prices for all stations and regions using traditional & proposed mechanism over the given time period.

Finally, Fig. 11 summarizes the daily unscheduled and scheduled EV charging cost in all regions. It is evident from the figure that charging cost is assigned to each vehicle as per individualized power demand profiles obtained form optimization facility, which are subject to hourly price function obtained from day-ahead electricity market. For example, the unscheduled charging cost of vc_{s_1} using $\hat{r}$ is comparatively lower, which reflects that vehicles in this particular station have drawn comparatively more power. However, the scheduled cost using $\tilde{r}$ is lower showing that this charging station is accommodating less number of EV as compared to other stations operating under same DSO. Table 2 provides a detailed cost comparison of EV charging over the given time interval. Cost profiles of unscheduled and scheduled cases elucidate that total unscheduled cost of each charging region is equal to unscheduled cost. However, the scheduled cost of each charging station is different due to individualized price profiles obtained by using proposed mechanism. Approximately, from 0.69-6.55% cost saving is achieved by using the proposed cost calculation mechanism.

VIII. CONCLUSION

This work proposes a novel mechanism for calculating EV charging prices with the objective of cost reduction and power system stability. The primary objective was to minimize EV charging cost along with overall peaks in distribution system, so that the cost incurred by each charging station is non-discriminatory. For evaluation purposes, the proposed mechanism is applied on a real time test case of a moderate size and the results are compared with traditional approach. Where, traditional EV charging stations operated under the same

DSO receive the "traditional pricing policy". The proposed work considers two cases: (i) EV are charged on FCFS basis, and (ii) scheduled charging patterns have been obtained from optimization facility. Then the EV charging cost is calculated on the basis of traditional and proposed pricing mechanism. From results, it is clear that customized cost profiles obtained from proposed mechanism have comparatively more savings (Table 2).

From analytical and simulation results, it can be concluded that traditional pricing mechanism can cause synchronization of EV load consumption patterns causing rebound peaks. In this regard, the proposed work has advantages over the traditional work which can increase the load factor and reduce the power losses. The results presented in this paper has drawn using realistic EV charging patterns. However, the actual charging behaviors in response to market clearing prices are complex and difficult to predict, accurately. Therefor, it is difficult to draw a general conclusion which can be applied to other group of EVs. Despite, the results presented in the proposed work are informative in that they highlight the associated problems with traditional pricing mechanism. One possible limitation of this work is that it does not directly facilitate the EV charing users, rather than it allows that market distributors to adopt such types of mechanisms to take long-term mutual benefits.

APPENDIX

PROOF OF LEMMA 1

Let suppose that in response to a day-ahead pricing signal, which is usually obtained from energy retailer, EV charging cost using eq. (25) is calculated. From Fig (3), it can be seen that utility price signal is dynamic in nature, which is designed on the basis of aggregated load demand. As a result, the total revenue is calculated. In our proposed work, we consider same price signal and aggregated & individual load consumption profiles of all EV stations and calculate separate price signals (eq. 15) for all stations. In this case, it is again expected that total cost in response to consumed load must remain same. In other sense, the condition eq. 18 must be satisfied. Otherwise, the proposed mechanism will fail in achieving homogeneous price policies, as shown in Figs. 9, 10.

$$\begin{aligned}&\big\{(P_{i_1,t_1} \times \mu_{i_1,t_1} \times \hat{r}_{t_1}) + (P_{i_2,t_2} \times \mu_{i_2,t_2} \times \hat{r}_{t_2}) +, \ldots,\\ &\quad (P_{\mathcal{U},T} \times \mu_{\mathcal{U},T} \times \hat{r}_T)\big\} = \big\{(P_{i_1,t_1} \times \mu_{i_1,t_1} \times \delta_{i_1,t_1})\\ &\quad +(P_{i_2,t_2} \times \mu_{i_2,t_2} \times \delta_{i_1,t_1}) +, \ldots, (P_{\mathcal{U},T} \times \mu_{\mathcal{U},T} \times \delta_{\mathcal{U},T})\big\}\end{aligned} \tag{30}$$

Eq. 30 shows that for any EV charging station over time t, the proposed algorithm can calculate charging price for that particular station without violating equality condition. It can be seen from Fig. 12 that price signals are dynamic, which depend on power consumption ratios and market price. It means, the EV charging cost would be based on actual consumption regardless to the aggregated load based price.

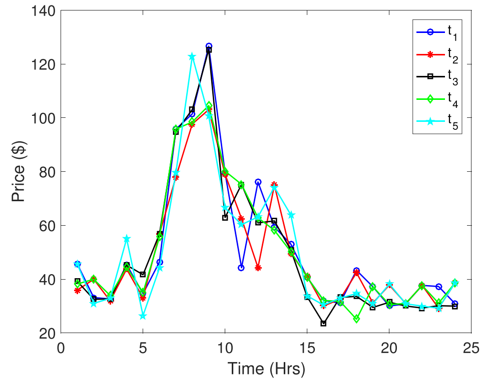


FIGURE 12. Aggregated price signals for EV charging stations using proposed mechanism over the given time period.

REFERENCES

[1] M. Kezunovic, S. T. Waller, and I. Damnjanovic, "Framework for studying emerging policy issues associated with PHEVs in managing coupled power and transportation systems," in *Proc. IEEE Green Technol. Conf.*, Apr. 2010, pp. 1–8.

[2] L. Yao, W. H. Lim, and T. S. Tsai, "A real-time charging scheme for demand response in electric vehicle parking station," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 52–62, Jan. 2017, doi: 10.1109/TSG.2016.2582749.

[3] Y.-W. Chen and J. M. Chang, "Fair demand response with electric vehicles for the cloud based energy management service," *IEEE Trans. Smart Grid*, vol. 9, no. 1, pp. 458–468, Jan. 2018, doi: 10.1109/TSG.2016.2609738.

[4] A. Awad, M. Shaaban, T. El-Fouly, E. El-Saadany, and M. Salama, "Optimal resource allocation and charging prices for benefit maximization in smart PEV-parking lots," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Chicago, IL, USA, Jul. 2017, p. 1, doi: 10.1109/PESGM.2017.8273903.

[5] *Electric Vehicle Charging Station Data*. Accessed: Jul. 20, 2019. [Online]. Available: https://www.nyserda.ny.gov/Researchers-and-Policymakers/Electric-Vehicles/Resources/Electric-Vehicle-Charging-Station-Data

[6] A. M. A. Haidar, K. M. Muttaqi, and M. H. Haque, "Multistage time-variant electric vehicle load modelling for capturing accurate electric vehicle behaviour and electric vehicle impact on electricity distribution grids," *IET Gener., Transmiss. Distrib.*, vol. 9, no. 16, pp. 2705–2716, Dec. 2015.

[7] C. Le Floch, F. Belletti, and S. Moura, "Optimal charging of electric vehicles for load shaping: A dual-splitting framework with explicit convergence bounds," *IEEE Trans. Transport. Electrific.*, vol. 2, no. 2, pp. 190–199, Jun. 2016, doi: 10.1109/TTE.2016.2531025.

[8] D. A. Chekired, L. Khoukhi, and H. T. Mouftah, "Decentralized cloud-SDN architecture in smart grid: A dynamic pricing model," *IEEE Trans Ind. Informat.*, vol. 14, no. 3, pp. 1220–1231, Mar. 2018.

[9] C. D. Korkas, S. Baldi, S. Yuan, and E. B. Kosmatopoulos, "An adaptive learning-based approach for nearly optimal dynamic charging of electric vehicle fleets," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 7, pp. 2066–2075, Jul. 2018, doi: 10.1109/TITS.2017.2737477.

[10] Q. Chen, F. Wang, B.-M. Hodge, J. Zhang, Z. Li, M. Shafie-Khah, and J. P. S. Catalao, "Dynamic price vector formation model-based automatic demand response strategy for PV-assisted EV charging stations," *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 2903–2915, Nov. 2017.

[11] S. S. Raghavan, "Impact of demand response on electric vehicle charging and day ahead market operations," in *Proc. IEEE Power Energy Conf. Illinois (PECI)*, Urbana, IL, USA, Feb. 2016, pp. 1–7, doi: 10.1109/PECI.2016.7459218.

[12] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid integration of electric vehicles and demand response with customer choice," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 543–550, Mar. 2012.

[13] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166–2173, Dec. 2012.

[14] S. Zhou, Z. Wu, J. Li, and X.-P. Zhang, "Real-time energy control approach for smart home energy management system," *Electr. Power Compon. Syst.*, vol. 42, nos. 3–4, pp. 315–326, Feb. 2014.

[15] A. Ul-Haq, C. Cecati, and E. El-Saadany, "Probabilistic modeling of electric vehicle charging pattern in a residential distribution network," *Electr. Power Syst. Res.*, vol. 157, pp. 126–133, Apr. 2018.
[16] N. Rahbari-Asr, M.-Y. Chow, J. Chen, and R. Deng, "Distributed real-time pricing control for large-scale unidirectional V2G with multiple energy suppliers," *IEEE Trans Ind. Informat.*, vol. 12, no. 5, pp. 1953–1962, Oct. 2016, doi: 10.1109/TII.2016.2569584.
[17] Y. Liu, S. Gao, X. Zhao, S. Han, H. Wang, and Q. Zhang, "Demand response capability of V2G based electric vehicles in distribution networks," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur. (ISGT-Europe)*, Turin, Italy, Sep. 2017, pp. 1–6, doi: 10.1109/ISGTEurope.2017.8260332.
[18] F. Rassaei, W.-S. Soh, and K.-C. Chua, "Demand response for residential electric vehicles with random usage patterns in smart grids," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1367–1376, Oct. 2015, doi: 10.1109/TSTE.2015.2438037.
[19] C. Le Floch, F. Belletti, S. Saxena, A. M. Bayen, and S. Moura, "Distributed optimal charging of electric vehicles for demand response and load shaping," in *Proc. 54th IEEE Conf. Decis. Control (CDC)*, Osaka, Japan, Dec. 2015, pp. 6570–6576, doi: 10.1109/CDC.2015.7403254.
[20] E. Akhavan-Rezai, M. F. Shaaban, E. F. El-Saadany, and F. Karray, "Managing demand for plug-in electric vehicles in unbalanced LV systems with photovoltaics," *IEEE Trans Ind. Informat.*, vol. 13, no. 3, pp. 1057–1067, Jun. 2017, doi: 10.1109/TII.2017.2675481.
[21] E. Akhavan, M. Shaaban, E. El-Saadany, and F. Karray, "New EMS to incorporate smart parking lots into demand response," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Chicago, IL, USA, Jul. 2017, p. 1, doi: 10.1109/PESGM.2017.8274030.
[22] A. Chiş, J. Lundén, and V. Koivunen, "Reinforcement learning-based plug-in electric vehicle charging with forecasted price," *IEEE Trans. Veh. Technol.*, vol. 66, no. 5, pp. 3674–3684, May 2017, doi: 10.1109/TVT.2016.2603536.
[23] O. Hafez and K. Bhattacharya, "Integrating EV charging stations as smart loads for demand response provisions in distribution systems," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1096–1106, Mar. 2018, doi: 10.1109/TSG.2016.2576902.
[24] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging: A customer's perspective," *IEEE Trans. Veh. Technol.*, vol. 62, no. 7, pp. 2919–2927, Sep. 2013.
[25] I. Momber, S. Wogrin, and T. G. S. Roman, "Retail pricing: A bilevel program for PEV aggregator decisions using indirect load control," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 464–473, Jan. 2016, doi: 10.1109/TPWRS.2014.2379637.
[26] Z. Xu, Z. Hu, Y. Song, W. Zhao, and Y. Zhang, "Coordination of PEVs charging across multiple aggregators," *Appl. Energy*, vol. 136, pp. 582–589, Dec. 2014.
[27] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging with energy storage in the electricity market," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 311–320, Mar. 2013.
[28] M. Ansari, A. T. Al-Awami, E. Sortomme, and M. A. Abido, "Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 261–270, Jan. 2015.
[29] M. S. Kuran, A. Carneiro Viana, L. Iannone, D. Kofman, G. Mermoud, and J. P. Vasseur, "A smart parking lot management system for scheduling the recharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2942–2953, Nov. 2015.
[30] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sep. 2012.
[31] L. Jian, X. Zhu, Z. Shao, S. Niu, and C. C. Chan, "A scenario of vehicle-to-grid implementation and its double-layer optimal charging strategy for minimizing load variance within regional smart grids," *Energy Convers. Manage.*, vol. 78, pp. 508–517, Feb. 2014.
[32] M. Alizadeh, H.-T. Wai, M. Chowdhury, A. Goldsmith, A. Scaglione, and T. Javidi, "Optimal pricing to manage electric vehicles in coupled power and transportation networks," *IEEE Trans. Control Netw. Syst.*, vol. 4, no. 4, pp. 863–875, Dec. 2017, doi: 10.1109/TCNS.2016.2590259.
[33] M. Alizadeh, H.-T. Wai, A. Scaglione, A. Goldsmith, Y. Y. Fan, and T. Javidi, "Optimized path planning for electric vehicle routing and charging," in *Proc. 52nd Annu. Allerton Conf. Commun., Control, Comput. (Allerton)*, Monticello, IL, USA, Sep. 2014, pp. 25–32, doi: 10.1109/ALLERTON.2014.7028431.
[34] M. H. Amini, J. Mohammadi, and S. Kar, "Distributed holistic framework for smart city infrastructures: Tale of interdependent electrified transportation network and power grid," *IEEE Access*, vol. 7, pp. 157535–157554, 2019, doi: 10.1109/ACCESS.2019.2950372.
[35] L. Ye, L. Zhao, S. Dong, and S. Chen, "Dispatch in electric vehicles embedded virtual power plants considering safety constraints," in *Proc. IEEE 3rd Int. Conf. Circuits, Syst. Devices (ICCSD)*, Chengdu, China, Aug. 2019, pp. 143–147, doi: 10.1109/ICCSD.2019.8843077.
[36] A. M. Farid, "Symmetrica: Test case for transportation electrification research," *Infrastruct. Complex.*, vol. 2, no. 1, p. 5, Oct. 2015.
[37] A. M. Farid, "Electrified transportation system performance: Conventional versus online electric vehicles," in *The On-Line Electric Vehicle*. Cham, Switzerland: Springer, 2017, pp. 279–313.
[38] H. Turker and S. Bacha, "Optimal minimization of plug-in electric vehicle charging cost with vehicle-to-home and vehicle-to-grid concepts," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10281–10292, Nov. 2018, doi: 10.1109/TVT.2018.2867428.
[39] S. F. Bush, "Demand-response and the advanced metering infrastructure," in *Smart Grid: Communication-Enabled Intelligence for the Electric Power Grid*. Hoboken, NJ, USA: Wiley, 2014, doi: 10.1002/9781118820216.ch7.
[40] S. Al-Rubaye, A. Al-Dulaimi, S. Mumtaz, and J. Rodriguez, "Dynamic pricing mechanism in smart grid communications is shaping up," *IEEE Commun. Lett.*, vol. 22, no. 7, pp. 1350–1353, Jul. 2018, doi: 10.1109/LCOMM.2018.2822798.
[41] S.-G. Yoon, Y.-J. Choi, J.-K. Park, and S. Bahk, "Stackelberg-game-based demand response for at-home electric vehicle charging," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4172–4184, Jun. 2016, doi: 10.1109/TVT.2015.2440471.
[42] C. Li, X. Yu, W. Yu, G. Chen, and J. Wang, "Efficient computation for sparse load shifting in demand side management," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 250–261, Jan. 2017, doi: 10.1109/TSG.2016.2521377.
[43] K. Qian, C. Zhou, and Y. Yuan, "Impacts of high penetration level of fully electric vehicles charging loads on the thermal ageing of power transformers," *Int. J. Elect. Power Energy Syst.*, vol. 65, pp. 102–112, Feb. 2015.
[44] *New York Independent System Operator*. Accessed: Sep. 7, 2019. [Online]. Available: https://www.nyiso.com/public/index.jsp
[45] W. Su and M.-Y. Chow, "Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck," *Appl. Energy*, vol. 96, pp. 171–182, Aug. 2012.
[46] W. Su and M.-Y. Chow, "Performance evaluation of a PHEV parking station using particle swarm optimization," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2011, pp. 1–6.
[47] W. Su and M.-Y. Chow, "Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 308–315, Mar. 2012.
[48] Z. Zhao, W. Cheol Lee, Y. Shin, and K.-B. Song, "An optimal power scheduling method for demand response in home energy management system," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1391–1400, Sep. 2013.
[49] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1244–1252, Sep. 2012.
[50] N. Kinhekar, N. P. Padhy, and H. O. Gupta, "Multiobjective demand side management solutions for utilities with peak demand deficit," *Int. J. Elect. Power Energy Syst.*, vol. 55, pp. 612–619, Feb. 2014.
[51] *Public Electric Vehicle (EV) Charging Stations Within Connecticut From US Department of Energy*. Accessed: Sep. 7, 2019. [Online]. Available: https://catalog.data.gov/dataset/electric-vehicle-charging-stations

MUHAMMAD BABAR RASHEED received the master's and Ph.D. degrees from COMSATS University, Islamabad, in 2013 and 2017, respectively. He is currently working as an Assistant Professor with the Department of Electronics and Electrical Systems, The University of Lahore, Pakistan. He has authored over 25 articles in well reputed journal and conference proceedings and supervised/supervising more than ten students in their final year projects and theses. His research interests include LP, NLP, heuristic optimizations, machine learning, smart grids, electric vehicles, and demand response. He is an active Reviewer of many esteemed journals and conferences, including the IEEE TheRANSACTIONS, IEEE ACCESS, the IEEE TRANSACTIONS ON INDUSTRY APPLICATION SYSTEMS, *Applied Energy*, and *Energies*.

MUHAMMAD AWAIS received the B.S. degree in electronics and communication from The University of Lahore, Lahore, in 2012, and the M.S. degree in electrical engineering from the COMSATS Institute of Information Technology, Islamabad, Pakistan, in 2015. He is currently pursuing the Ph.D. degree in computer science with COMSATS University Islamabad, Lahore. He is also serving as an Assistant Professor with the Faculty of Engineering and Technology, The University of Lahore. He has been published more than ten research publications in well reputed international journals and conferences. His research interests include but are not limited to smart grid energy management, artificial intelligence in home automation, energy efficiency in smart homes, and heuristic and mathematical optimization techniques in the smart grid.

THAMER ALQUTHAMI received the Ph.D. degree in electrical engineering with minor in mathematics from the Georgia Institute of Technology. He is an experienced Assistant Professor with a demonstrated history of working in the higher education and industry. His expertise areas are smart grids, renewable energy, power system operation and control, complex system modeling and simulation, energy audit, energy efficiency and savings, and data analytics. He is skilled in PSCAD/EMTDC, Python, PTI/PSSE, RTDs, building automation implementation, R-statistics, and C++.

IRFAN KHAN (Member, IEEE) received the Ph.D. degree in electrical and computer engineering from Carnegie Mellon University, USA. He is currently an Assistant Professor of Practice with the Electrical and Computer Engineering Department, Texas A&M University (TAMU), TX, USA. He has published more than 20 refereed journal and conference papers in the smart energy systems related areas. His current research interests include control and optimization of smart energy networks, optimization of energy storage systems, DC microgrids, smart grids, and renewable energy resources. He is a member of PES. He is the Vice Chair for the IEEE PES Joint Chapter of Region 5 Galveston Bay Section (GBS), where his responsibilities are to organize presentations, invite renowned experts from power and energy background for presentations to GBS members. He is the Registration Chair at the IEEE sponsored International Symposium on Measurement and Control in Robotics that was organized at the University of Houston Clear Lake on September 19–21, 2019. He is an active Reviewer of many esteemed journals and conferences, including the IEEE Transactions on Power Systems, the IEEE Transactions on Smart Grids, IEEE Access, the IEEE Transactions on Industry Application Systems, *IET Smart Grids, Electrical Power Components and Systems*, and *Energies*.