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RESEARCH ARTICLE

Optimal EV Charging Strategy for Distribution Networks Load Balancing in a Smart Grid Using Dynamic Charging Price

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ABSTRACT The adoption of electric vehicles (EVs) promises a reduction of carbon emissions and a crucial step towards a cleaner environment. While more EVs are expected to replace internal combustion engine vehicles to operate on the road worldwide, their adoption is inhibited by factors such as high power demand. Unregulated or poorly regulated charging of EVs can cause grid instability, especially in grids that were not initially designed to handle the charging of EVs. This calls for leveraging the available grid resources to control the charging of EVs in a manner that ensures optimal grid operation. This work proposes a distribution network-level dynamic pricing strategy for charging EVs to optimally utilize the distribution network and balance the load between residential and commercial/industrial distribution networks. Different EV charging probabilities that cause the EV load to differ from the optimal state with a mean average percentage error (MAPE) as high as 30% are explored. Simulation results show that with the dynamic pricing strategy as an incentive to the EVs users, EVs charging load will contribute to the optimal grid resources utilization.

INDEX TERMS Distribution networks, electric vehicles, optimization, smart grids.

I. INTRODUCTION

The global market of electric vehicles (EVs) has been growing exponentially in the last decade [1]. In 2018, the International Energy Agency (IEA) made predictions that 130 million EVs are expected to be operating on the road worldwide in 2030 [2]. Regardless of the observed progress in the adoption of EVs, there are factors that inhibit the adoption to reach its full potential. High costs and a shortage of charging stations are some of those factors [3]. Many distribution networks were not initially designed to accommodate the EVs, therefore incorporating charging of EVs in such networks will create an additional load that will cause grid instability [4]. This calls for coordinated EV charging mechanisms that will help to reduce their negative impact on the grid and increase its efficiency [3].

The EVs can be classified into two major categories namely: plug-in hybrid EVs (PHEVs) and battery EVs (BEVs). The PHEVs use both fossil fuels and battery energy for propulsion, while BEVs run solely on the energy from the batteries [3]. PHEVs' driving range and fuel economy are competitive compared to that of internal combustion engine vehicles (ICEVs) [4]. On top of that, compared to ICEVs, EVs are cheaper to operate and maintain because they have fewer moving parts and use little or no fossil fuels [4]. Since EVs can be powered with electricity generated from renewable sources, shifting from ICEVs to EVs is also seen as one of the most effective methods to reduce carbon emission [5].

On the other hand, an increasing number of EVs poses a challenge when it comes to data processing issues in a

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smart grid, such as charging information collection [6]. The penetration of EVs into the market brings many advantages that include less usage of natural gas, leading to the reduction of carbon emissions. However, as the number of EVs increases, the power utilities are likely to encounter the challenge of keeping up with the grid load demand. In addition to more power generation being needed, the old distribution networks may have a limited capacity to handle the load since they were not designed to cater for EV load. While increasing the capacity of the distribution network may be a good solution, it is an expensive and time-consuming process.

Most of the research in the literature models the likelihood of EVs to charge based on the state of charge [7], [8], [9]. Assumptions about the EVs' power consumption in a given mileage, trips made per day, etc., have to be made. If the state of charge reaches the minimum allowed value, the EV is charged. Besides the state of charge, the other factors that influence the area of charging for the user include the distance to the charging station, and the time available for charging. This work proposes optimal EVs' charging and load-balancing framework between residential and commercial/industrial areas. We propose a dynamic charging price mechanism to attract EV users to charge their EVs in optimal locations at optimal times, to better utilize the distribution network. The main contributions are as follows:

- Motivated by the load profile of the distribution networks in residential and commercial/industrial areas, we introduce the first method that seeks to optimally distribute the load between the distribution networks through the EV charging price incentive-controlled charging mechanism.
- We design an EV charging price algorithm that utilizes the discrete smart grid time of use (TOU) prices to set the dynamically changing EV charging prices based on the distribution network's load to attract the EV load that complements the conventional load to better utilize the distribution networks.
- We test our method using the realistic TOU pricing structure and the possible EVs charging probabilities to determine its impact on optimizing the network load. The proposed EV charging pricing strategy proves to optimize the distribution network by filling the valleys and shaving the peaks in both residential and commercial loads.

The remainder of this paper is organized as follows. Section II covers the related work done in literature to optimally integrate the EVs into the smart grid. In Section III, the procedure for balancing the load between the residential and commercial areas through charging information sharing and dynamic pricing method is outlined. Section IV presents the results obtained by testing the proposed method and the discussion of the results. The paper is finally concluded in Section V.

II. RELATED WORK

With the increasing penetration of EVs into the market, optimal integration of EVs into smart grids has gained the attention of many researchers worldwide. Sohail et al. [10] investigated the effect of uncoordinated EV charging on the residential distribution network load, with different EV penetration levels. They modelled the EV load by using a modified polynomial ZIP load (a load that has a combination of constant impedance (Z), constant current (I), and constant power (P) components) model. They found that increased EV penetration will result in under-voltage and over-current during peak hours if the EV charging is not coordinated. They made further investigation in [11] with TOU pricing in place. The results show that most of the EVs would be charged when the price is lowest, thereby giving rise to the new peak.

Authors in [12] analysed the energy load profiles in residential areas for TOU users, based on the data taken from the energy meters. They were able to establish that EV owners prefer to charge their electric vehicles when the TOU price is at its lowest (at midnight). This gives rise to the two electricity demand peaks in the residential area with the presence of EVs. The first peak which is between 18:00 and 20:00 results from the usual household load, while the midnight peak comes from the charging of electric vehicles. Users can charge the EVs at midnight by setting the charging time using the smartphone applications. Authors in [13] analysed the retail buildings' load in the presence of EV charging stations. They predict the EV load to peak between 12:00 and 18:00 when the load of the building is also highest, since the EV users prefer to charge their EVs while doing the shopping. The charging demand is lowest between 20:00 and 06:00. This also has the potential to destabilize the grid as the number of EVs increases.

Many optimization strategies with the main objectives that include stabilizing the grid and lowering the EVs charging cost are proposed. Some methods target to influence the EVs charging behaviour by introducing new charging pricing strategies, while other methods formulate and optimize different objective functions. Qureshi et al. [14], [15] present a menu-based EVs charging pricing using mobile charging stations (MCS). They divide the area covered with EVs into smaller zones. When an EV user in a given zone requests to charge an EV, the charging station operator solves an optimization problem to determine the menu of prices for the user to choose from, by minimizing the cost of charging and the number of MCS required. Compared to a flat pricing strategy, this method proved to lower the cost of charging.

Saha et al. [16] present a game theory-based optimal charging and discharging of EVs to set the charging and discharging prices that encourage EVs to charge during off-peak hours and to discharge during peak hours. Simulated over a 24-hour period data, the method was found to reduce the total cost of charging for the users while boosting the revenue of the grid operator. In [17], authors use Non-dominated Sorting Genetic Algorithm 2 (NSGA2) to reduce the customers' charging costs, increase charging stations' profits and reduce peak-to-valley differences in the commercial grid load. They introduce dynamic charging service fees that are set depending on the grid load for each hour.

Authors in [18] propose a centralized coordinated model to schedule the charging of electric vehicles in a smart grid. The whale optimization algorithm is used to optimize the multi-objective problem with an aim to minimize charging cost, load variance, and power loss. The model is tested on an IEEE-33 bus distribution network with a total power of 3.72MW. The assumed number of electric vehicles is 500, each with a maximum power of 8.90KW. The performance of their optimization strategy surpasses that one of Grey Wolf Optimization (GWO), Binary Artificial Transmutation (BAT), Particle Swarm Optimization with Grey Wolf Optimizer (PSOGWO) and Grey Wolf Optimizer with Chaotic Search (GWOCS). In [19], they consider the integration of electric vehicles into industrial and residential regions with the presence of photo-voltaic distributed generations. They use a whale optimization algorithm in conjunction with a Gravitational Search Algorithm (GSA) with an objective to minimize power loss, voltage stability and carbon emission. The model is tested on the IEEE-33 bus distribution test network. They assumed the presence of 1,000 electric vehicles. Their model's performance supersedes uncoordinated charging, whale optimization algorithm used alone, genetic algorithm used alone and particle swarm algorithm used alone.

In addition to aiming to stabilize the grid by minimizing power loss and improving voltage stability, [20] also considers installation cost, operational cost and carbon emission objectives. The authors propose a framework based on multi-objective optimization in different categories to integrate Distribution Generation (DG) units, Battery Energy Storage Systems (BESS), and Electric Vehicle Charging Station (EVCS) into the smart grid. They use Genetic Algorithm (GA) and Whale Optimization Algorithm (WOA) to determine the DG and BESS optimal locations and sizes, and reinforcement learning to determine the optimal EV charging stations locations. based on optimal Photo-voltaic (PV)-DGs and BESS locations and sizes. The proposed algorithm is tested on IEEE 33- and 118-bus distribution networks.

In [21], a charging and discharging control strategy based on particle swarm optimization and user decision to charge is proposed. Real electricity prices during peak and off-peak times are taken into consideration. The objective is to have the best discharging cost and charging cost for each electric vehicle. The authors run experiments on an IEEE-33 bus with a single charging station. This may not be closer to mimicking the real power grid.

Shang et al. [22] propose a consortium blockchain-based electric vehicles charging and discharging in a smart grid. They optimize a dual objective function using an improved grey wolf optimization algorithm. The objectives optimized are the cost of charging to the electric vehicle owner at a certain time t and the load variance. This helps to avoid destabilization of the grid while encouraging users to save costs of charging by charging at certain times.

In [8], authors propose an optimized charging schedule for a plug-in electric vehicle on a PV-powered and grid-connected charging station. With the main objective of minimizing the cost of charging an electric vehicle, the prediction of day-ahead solar generation is made using an artificial neural network, and the data is integrated into the scheduling algorithm. They also use day-ahead solar generation prediction to reduce overall grid costs and the burden on the grid. They compare the proposed algorithm's performance with uncontrolled charging with only grid power, uncontrolled charging with grid power and the PV power source, and optimized charging with grid power only. The proposed algorithm surpasses the benchmark.

Authors in [23] propose an integration of electric vehicles and distributed generators into the grid using the battle royale optimization method. The method is implemented on CIGRE 14-bus MV distribution network. The authors explore the performance of the grid in the following cases: when DGs are integrated into a simple network, when EVs are integrated into a simple network, and when both DGs and EVs are integrated into a network. The performance of the Battle Royale Optimization (BRO) algorithm is compared to that of GA, PSO and Accelerated PSO (APSO) on these three cases.

Authors in [24] propose a centralized matpower power flow algorithm for charging EVs. They came up with a power flow model on the branch that includes the plug-in EV charging station and tested the model on the 123 IEEE test system. They considered the following three scenarios: one charging station located on a single bus in the distribution network, three buses in the network having charging stations, and lastly, multiple charging stations in a city, considering the vehicles' distribution. Authors in [25] compare different classification machine learning algorithms when it comes to directing EVs to the most effective charging locations on a network with twelve different types of charging stations. Best locations are determined by maximizing the effectiveness of the distribution network and minimizing the cost of charging. The models compared are decision trees, random forest (RF), support vector machine (SVM), k-nearest neighbours (KNN), deep neural network (DNN) and long short-term memory (LSTM). The models' ability to select charging stations with the best charging speed was also determined. In both cases, RF and LSTM outperformed other models with the best accuracy.

Authors in [26] propose a blockchain-based EV charging method to preserve the privacy of EV users. Authors assume that charging stations are run by independent users, hence they charge different prices for charging EVs at a given time. In their protocol, an EV broadcasts the charging-

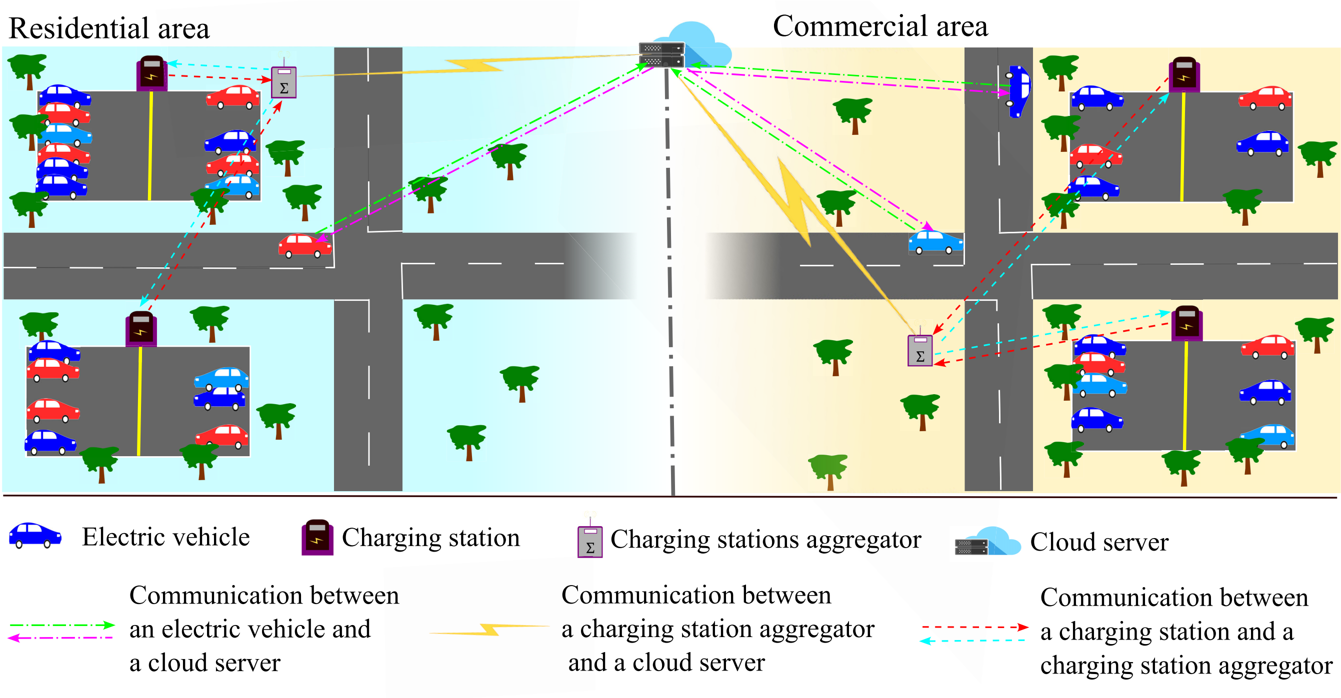


FIGURE 1. High-level schematic of the EV-charging load-balancing framework.

request message that is received and processed by the charging stations in the location specified by the message. The charging stations bid for the charging price, and the winning charging station communicates directly with the EV. They propose the use of blockchain for transparency and to verify the biddings. The EV can only expose its location to the best bidder after the bidding process.

In [7], the EV charging load in a residential area is modelled, and the model is analysed based on the actual charging behaviour data for the residential area in Shanghai. The model is based on the following: the establishment of power consumption vs distance relationship using Advanced Vehicle Simulator (ADVISOR) simulation platform, the approximation of the distribution function that shows the EVs' return-to-home times using the National Household Travel Survey (NHTS) data, and the construction of a mileage model that is used to infer the state of charge (SOC) distribution and hence the charging behaviour. The proposed model could fit the actual charging behaviour for the residential area selected in Shangai.

Authors in [27] propose a charging strategy for EVs in old residential areas, based on two optimization layers. They first came up with the LSTM model to predict the departure time for each user based on the historical data that includes the departure time for each user, collected by the charging controller. They define the objective function as the total user satisfaction, which is the ratio of users who gain a SOC $\geq 80\%$ of the target power at departure time, to the total number of users. The first layer of optimization uses PSO to obtain total user satisfaction based on the electricity allocated to each EV. The second layer uses GA, based on the total power distribution of each EV.

While these methods contribute to the knowledge that will drive optimal grid use in the presence of EVs, the possibility of balancing the load between the distribution grids remains unexplored. This work seeks to extend to this dimension to further widen the possible ways of optimal grid usage.

III. DYNAMIC PRICING STRATEGY AND EVS CHARGING INFORMATION SHARING BETWEEN DISTRIBUTION NETWORKS

In smart power grids, the price of electricity is normally set based on the total grid load variation with time. Focusing deeper into the level of distribution grids, it is observed that different distribution grids have different patterns of power consumption. In as much as conventional TOU pricing helps to encourage better grid utilization, a mechanism to encourage optimal grid usage at the distribution grid level will further improve grid utilization and stability. This work presents a dynamic EV charging price mechanism that encourages an optimally distributed grid load by encouraging the charging of EVs to be distributed between residential and commercial areas. Figure 1 shows the high-level schematic of the proposed framework.

The region covered with charging stations is split into two area categories with different electricity consumption patterns: residential and commercial/industrial areas. A single charging stations aggregator for charging stations belonging to each area is proposed. The aggregator collects information from the charging stations such as the charging station

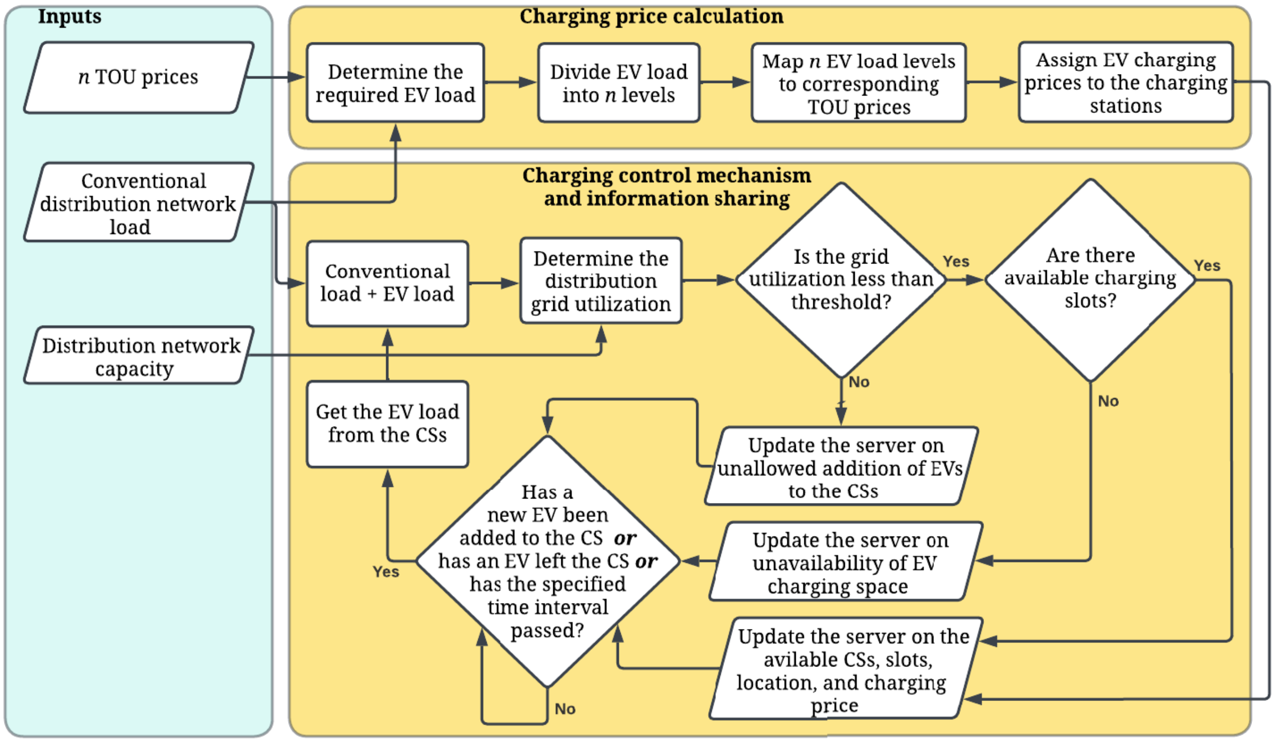


FIGURE 2. The flowchart of the proposed dynamic pricing strategy.

location, number of charging slots, power rating of each charging slot, which charging slots are in use at a given instant, etc. This information is shared with the cloud server so that it can be accessed by EV users anywhere.

We also present an algorithm that sets the EV charging price in each area for the next 12 hours, based on the conventional load pattern of a distribution network in each area and the desired EV charging load pattern for an optimally operating distribution network. The flowchart of the proposed methodology is shown in Figure 2.

We propose a central pricing strategy that sets the EV charging price for an area based on the consumption pattern of that area. The power consumption behaviour in an area is observed. After observing the consumption behaviour, the load pattern that must come from the charging of EVs in a manner that ensures optimal operation of a distribution network is determined. To achieve an optimal operation of the given distribution network, the charging activity of EVs is maximized when the conventional load is in its minimal state, and the charging activity is minimized when the conventional load is in its maximum state. The maximizing and minimizing of the charging of EVs at a given time is done by setting different charging prices that vary with the variation of load in a given distribution network.

These varying charging prices and the location information of the charging stations are made to be publicly available on the cloud server, where EV users can access them. Moreover, the users should be educated on the EV dynamic charging price behaviour to enable them to make good decisions as to when and where they charge their EVs, for the mutual benefit of both the grid operator and the EV users.

A charging station periodically sends its availability information to the aggregator in terms of its unique identification, location, and available slots. Charging availability information is also shared with the cloud server when a new EV is added to the CS or when an EV leaves the CS after charging. The aggregator sends this information to the cloud server together with the forecast charging price, where it can be accessed by EVs anywhere. The price revealed to the user is limited to 12 hours. An EV user that needs to charge has the flexibility of charging at the available charging spot on the CS of choice, considering the following factors: the distance to the CS, the charging price of each CS, and the CS availability.

A. CHARGING STATIONS AGGREGATOR LOAD

Consider a charging station **CS** represented by

$$\mathbf{CS} = \begin{bmatrix} S_{1,0} & S_{1,1} & \dots & S_{1,23} \\ S_{2,0} & S_{2,1} & \dots & S_{2,23} \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ S_{n,0} & S_{n,1} & \dots & S_{n,23} \end{bmatrix}, \tag{1}$$

where

$$S_{i,t} = \begin{cases} 1, & occupied \\ 0, & unoccupied \end{cases} \tag{2}$$

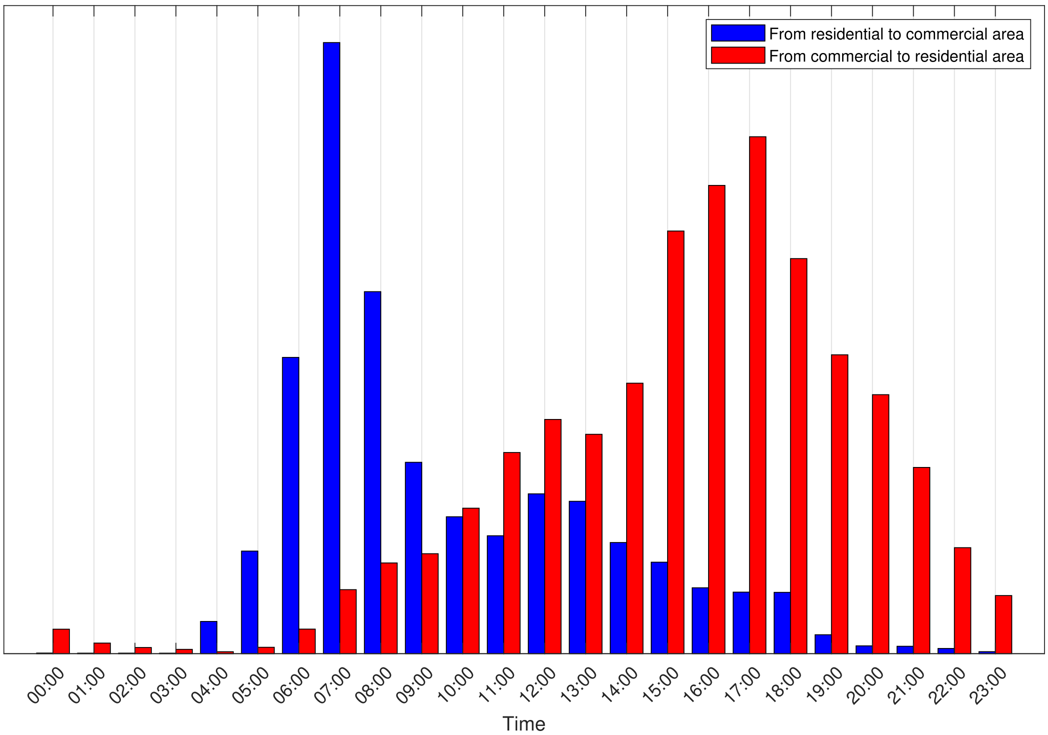


FIGURE 3. Vehicle travel behaviour between residential and commercial regions based on U.S. NHTS data.

is the availability of the i^{th} charging slot in an hourly interval $t \in [0, 23]$. The charging station's load l_t^{CS} at time t is given by

$$l_t^{CS} = \sum_{i=1}^{n} S_{i,t} \cdot l_{S_{i,t}}, \tag{3}$$

where $l_{S_{i,t}}$ is the load of the i^{th} slot at time t. The charging load y_t of the EVs in a distribution network with m charging stations at time t is given by

$$y_t = \sum_{i=1}^{m} l_{i,t}^{CS}. \tag{4}$$

B. THE DISTRIBUTION NETWORK LOAD

The distribution network load consists of electricity consumption from home appliances, machinery, etc. It varies with time and has a predictable pattern depending on the location of the distribution network, whether in the residential or commercial area. The charging of electric vehicles has the potential to alter the load pattern of the distribution network since EVs are mobile and can be charged anywhere convenient at a given time.

Let x_t be the conventional distribution grid load at time t. When the EVs are charged, the distribution load at a time t is given by

$$x_t + y_t \leq \kappa, \tag{5}$$

where κ is the maximum load that can be handled by the network.

The studies made in [12] and [13] show the load patterns in residential and commercial areas. The load can be approximated with the Gaussian mixture model (GMM). Gaussian component densities can be combined with a weighted sum to form a GMM [28]. In general, GMM can be expressed as follows:

Given the mean vector μ_i, $i = 1, \ldots, j$ covariance matrix Σ_i, and the components weights w_i, the GMM is given by

$$\Lambda(\mathbf{r}|\mu_i, \Sigma_i, w_i) = \sum_{i=1}^{j} w_i \lambda(\mathbf{r}|\mu_i, \Sigma_i), \tag{6}$$

where $\mathbf{r}$ is a data vector of dimension D and $\lambda(\mathbf{r}|\mu_i, \Sigma_i)$ are the component Gaussian densities given by

$$\lambda(\mathbf{r}|\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{\frac{D}{2}} |\Sigma_i|^{\frac{1}{2}}} \exp -\frac{1}{2}(\mathbf{r} - \mu_i)^{\mathsf{T}} {\Sigma_i}^{-1}(\mathbf{r} - \mu_i). \tag{7}$$

We further analyse the typical behaviour of vehicles commuting between residential and commercial areas in a day. For this purpose, we use the NHTS dataset [29]. Figure 3 shows the bar chart of commuting behaviour on a given weekday.

As shown in Figure 3, the number of cars that leave the residential area to the commercial/industrial areas peaks in the morning at around 07:00 hours, and the number of cars that leave the commercial/industrial areas to the residential area peak just before an evening at around 17:00 hours. This suggests that during the day, the cars spend most of the time in the commercial areas, and from evening till early morning, most cars are in the residential areas. Without proper control of when and where the EVs charge, distribution networks in the residential areas are likely to be overloaded in the evening and night times, while commercial areas distribution networks are likely to be overloaded during the day. A mechanism to balance the load between the distribution networks and to optimally utilize the network is required.

C. DYNAMIC CHARGING PRICE

In smart grids, TOU pricing is made in such a way that the unit prices vary according to the grid load at different times of the day. A time span of 24 hours is divided into q ranges such that for the total grid load $\{L_{\tau_1}, L_{\tau_2}, \ldots, L_{\tau_q}\}$ in time ranges $\{\tau_1, \tau_2, \ldots, \tau_q\}$ there exists discrete unit prices $\{P_{\tau_1}, P_{\tau_2}, \ldots, P_{\tau_q}\}, P_{\tau_\theta} \in \mathbf{P} = \{P_1, \ldots, P_n\}$, where $\mathbf{P}$ is a set of unique discreet prices. The pricing mechanism is global. The discrete unit prices are set in a manner that they are in direct proportion to the total grid load. That is, if the total grid load at a time range τ_θ is at the highest peak, then P_{τ_θ} is made in such a way that $P_{\tau_\theta} = \max(P_{\tau_1}, P_{\tau_2}, \ldots, P_{\tau_q})$. In the same manner, the unit price when the total grid load is at its minimum is $\min(P_{\tau_1}, P_{\tau_2}, \ldots, P_{\tau_q})$.

We use the existing, grid-specific TOU pricing structure to ease the practical implementation of the proposed pricing strategy shown step-by-step in Algorithm 1.

Algorithm 1 Dynamic Pricing for Charging EVs

Require: load profile $\mathbf{x}$, q TOU prices, ζ, κ

Divide $\mathbf{x}$ into 24-hour cycles
while cycles, **do**
  Evaluate $\mathbf{x}'$ based on Equation (8).
  Calculate δ_1 and δ_2 using Equations (9) and (10) respectively.
  Evaluate $\mathbf{y}'$ by minimizing $g(\mathbf{y}' + \mathbf{x}' + \delta_1 + \delta_2)$.
  Divide the values of $\mathbf{y}'$ into n ranges within the bounds of $\min(\mathbf{y}')$ and $\max(\mathbf{y}')$ to get $\mathbf{y}''$.
  Sort $\mathbf{y}''$ in descending order and the $\mathbf{P}$ in ascending order to get $\mathbf{y}''_\pi = \{y''_{\pi_d(1)}, \ldots, y''_{\pi_d(n)}\}$ and $\mathbf{P}_\pi = \{P_{\pi_a(1)}, \ldots, P_{\pi_a(n)}\}$, where π_d and π_a are permutations that sort $\mathbf{y}''$ and $\mathbf{P}$ in descending and ascending orders respectively.
  for i `in` $\{1, \ldots, n\}$ **do**
    Assign $y''_{\pi_d(i)}$ to $P_{\pi_a(i)}$
  end for
end while

Let κ be the distribution network capacity and $\mathbf{x} = (x_0, x_1, x_3, \ldots, x_{23})$ be the conventional load of the distribution network for 24 hours, sampled on an hourly interval. Evaluate $\mathbf{x}'$ with equation (8):

$$\mathbf{x}' = f(\mathbf{x}) = 2 \times \frac{\mathbf{x}}{\zeta} - 1, \tag{8}$$

where f normalizes $\mathbf{x}$ in the range $[1, -1]$ using ζ and 0 as the maximum and minimum thresholds respectively. ζ is chosen in such a way that $\max(\mathbf{x}) \leq \zeta < \kappa$. EVs can be seen as the mobile load that can be plugged when the distribution network is not highly utilized to fill the demand valley and keep the grid operating optimally. For valley filling and peak shaving, find δ_1 and δ_2 using equations (9) and (10) respectively, where $\max(\mathbf{x}')$ and $\min(\mathbf{x}')$ are the largest and the smallest element in $\mathbf{x}'$.

$$\delta_1 = 1 - \max(\mathbf{x}') \tag{9}$$

$$\delta_2 = -1 - \min(\mathbf{x}'). \tag{10}$$

Lastly, minimize $g(\mathbf{y}' + \mathbf{x}' + \delta_1 + \delta_2)$ subject to

$$-\mathbf{1} \leq \mathbf{y}' \leq \mathbf{1}. \tag{11}$$

Since $\mathbf{x}'$ has been normalized in the range $[1, -1]$ using equation (8), we solve a convex optimization problem by finding the minimum of $||\mathbf{y}' + \mathbf{x}' + \delta_1 + \delta_2||$ using the exponential cone solver, restricting the decision variable $\mathbf{y}'$ in the range $[1, -1]$.

δ_1 and δ_2 addition to $\mathbf{x}'$ is element-wise. $\mathbf{y}'$ is the normalized desired load that must come from the charging of EVs. We denormalize $\mathbf{y}'$ to get $\mathbf{y}$ using equation (12)

$$\mathbf{y} = f'(\mathbf{y}') = \zeta \times (\frac{\mathbf{y}' + 1}{2}). \tag{12}$$

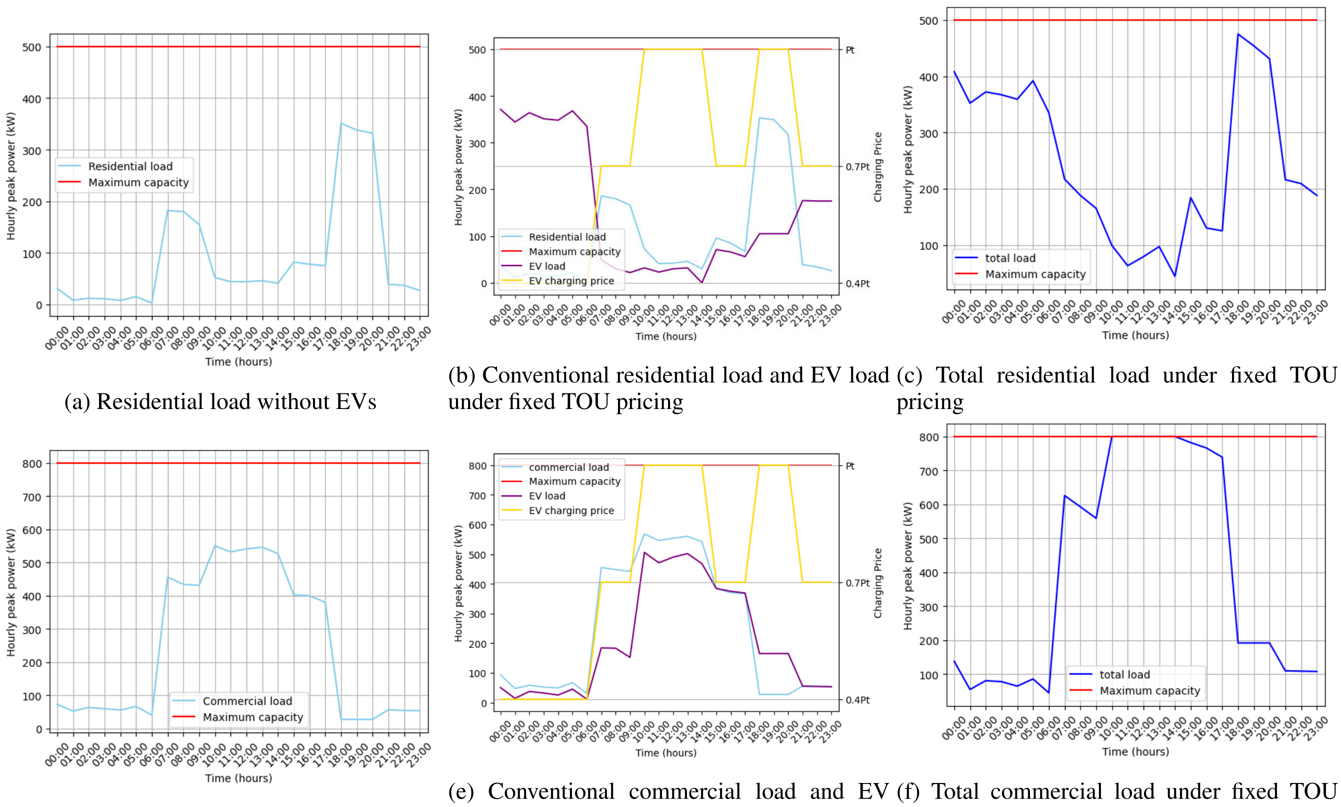
After obtaining the desired valley-filling load $\mathbf{y}$, the charging price is computed in the following manner. Using $\max(\mathbf{y})$ and $\min(\mathbf{y})$ as the upper and lower bounds respectively, $\mathbf{y}$ is divided into the number of levels that equal the number of the discrete unit prices $P_{\tau_1}, P_{\tau_2}, \ldots, P_{\tau_q}$. Allocate the lowest load to the highest price, the second lowest load to the second-highest price, and continue allocating loads until the highest load is allocated to the lowest price.

IV. RESULTS AND DISCUSSION

The decision to charge an EV is influenced by many factors. In as much as the charging price significantly affects the EVs charging load, there are conditions that can lead to charging some EVs when the charging price is not favourable. We therefore test our method using three different possible charging probabilities or load distributions for the given charging price.

We first show how the current pricing strategy affects the EVs charging behaviour in the absence of the charging optimization algorithm. We use the pricing mechanism shown in Table 1, inspired by [21]. We then show the simulation results of the EV load behaviour in the presence of the proposed strategy. We further investigate the probable EV load behaviour for the total EV load significantly less than or greater than the conventional load. The charging price and corresponding charging probabilities are given in Table 1.

Data generation, pricing method and testing are all implemented using Python programming language in a Visual Studio Code environment.



(a) Residential load without EVs

(b) Conventional residential load and EV load under fixed TOU pricing

(c) Total residential load under fixed TOU pricing

(d) Commercial load without EVs

(e) Conventional commercial load and EV load under fixed TOU pricing

(f) Total commercial load under fixed TOU pricing

FIGURE 4. **Residential and commercial conventional and EV load under fixed TOU pricing.**

TABLE 1. **EV charging prices and tested corresponding probabilities.**

Time	Price	Probability 1 EV load	Probability 2 EV load	Probability 3 EV load
00:00 - 07:00	0.4Pt	0.9	0.8	0.65
07:00 - 10:00 , 15:00 - 18:00, 21:00 - 0:00	0.7Pt	0.08	0.14	0.25
10:00 - 15:00 , 18:00 - 21:00	Pt	0.02	0.06	0.1

A. IN THE ABSENCE OF THE CHARGING OPTIMIZATION ALGORITHM

To demonstrate the effect of fixed TOU pricing that applies to all loads at different times, we adopt the pricing mechanism given in [21], summarized by the first two columns in Table 1. In the light of the studies made in [11], [12], and [13] on the residential and commercial areas load patterns in the presence of EVs, we show the EV load pattern as well as the conventional load in the residential and commercial areas in Figure 4.

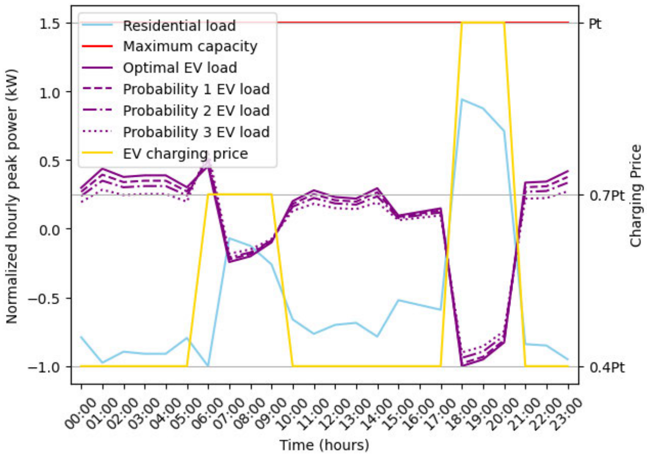
Conventional residential load is generated by using the GMM and the parameters are set to achieve the typical residential load pattern shown in Figure 4. We consider a residential distribution network with the capacity $\kappa = 500\ kW$ in the residential area with 350 kW peak demand. In the same manner, the conventional commercial load is generated using GMM in such a way that it follows a commercial load pattern. We consider a commercial distribution network with the capacity $\kappa = 800\ kW$ in the commercial area with 550 kW peak demand.

We first consider a case where the total EV load over the 24-hour period is approximately equal to the total conventional load. We observe from Figure 4b that the EV load reaches its peak when the unit price is lowest. The EV load is lowest when the conventional load is lowest during the hours around midday. During this time, the grid is less utilized. In the evening when the conventional load is at its peak, the total distribution network load may reach or exceed the maximum capacity of the grid.

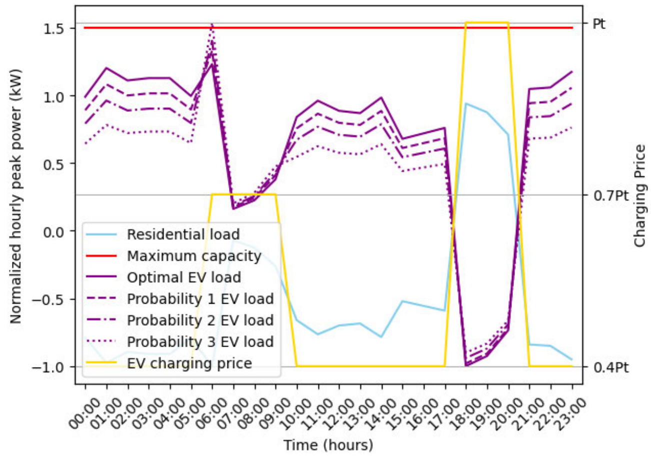
In the commercial area, the EV load peaks during the peak of the conventional load as shown in Figure 4e. The distribution network is much utilized during working hours, and less utilized thereafter. When the charging load increases, the commercial area distribution network will encounter congestion problems during the day and have less utilization of the resources at night. Figures 4c and 4f show the total load which is the sum of conventional load and EV charging load in the residential and commercial areas distribution networks respectively. From these Figures, it can be seen that the load varies significantly for peak and off-peak hours of each area, showing that in the absence of EVs charging optimization algorithm, the grid is poorly utilized.

B. IN THE PRESENCE OF THE CHARGING OPTIMIZATION ALGORITHM

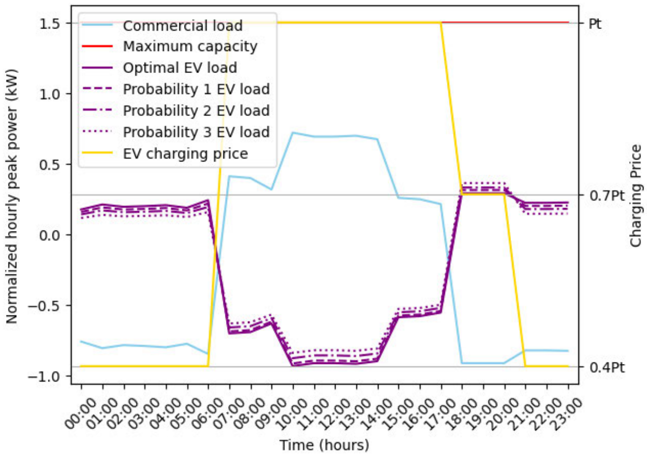
To show the effectiveness of the proposed dynamic charging strategy, we set the same peak and capacity values as in IV-A.



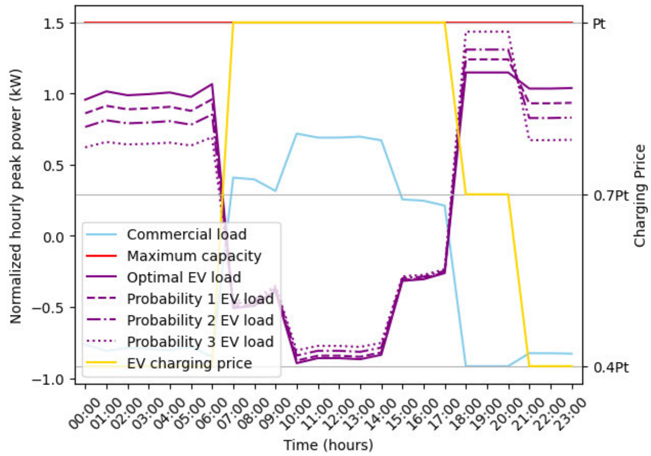
(a) Residential area EV load 25% lower than conventional load



(b) Residential area EV load 25% higher than conventional load



(c) Commercial area EV load 25% lower than conventional load



(d) Commercial area EV load 25% higher than conventional load

FIGURE 5. Varying EV load impact in the residential and commercial areas.

We further introduce parameter ζ, which is the maximum optimal load allowed on the grid, set at 80% of the distribution grid capacity.

1) RESIDENTIAL AREA LOAD ANALYSIS

By setting $\zeta = 0.8 \times \kappa = 400\ kW$, we use Equation (8) to transform $\mathbf{x}$ and κ. The optimal EV load pattern and the EV charging price are determined as stipulated in Section III-C. Based on the dynamically varying price, we compute the EV charging load pattern based on the probabilities given in Table 1. Figure 6 shows the optimal EV load pattern, EV charging price and all the load variations based on the probabilities given in Table 1. Figure 6b shows the total distribution network load pattern obtained by adding the conventional residential load with the probability 2 EV load.

Comparing Figures 4c and 6b, the distribution in load over the 24-hour period in Figure 6b is better than in 4c. The difference between the peak and trough is 431.00 kW and 58.24 kW for Figures 4c and 6b respectively, which can be seen in Figure 6c.

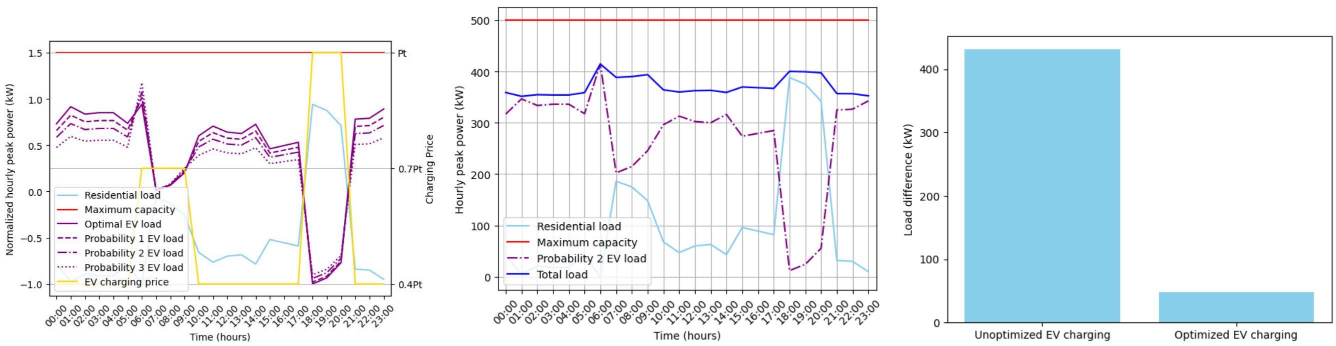
2) COMMERCIAL AREA LOAD ANALYSIS

For the commercial area load analysis, the same procedure followed in the residential area load analysis is repeated. The typical commercial load pattern is generated as shown in Figure 4d. Normalization is done on $\mathbf{x}$ and κ with $\kappa = 800\ kW$ and $\zeta = 640\ kW$.

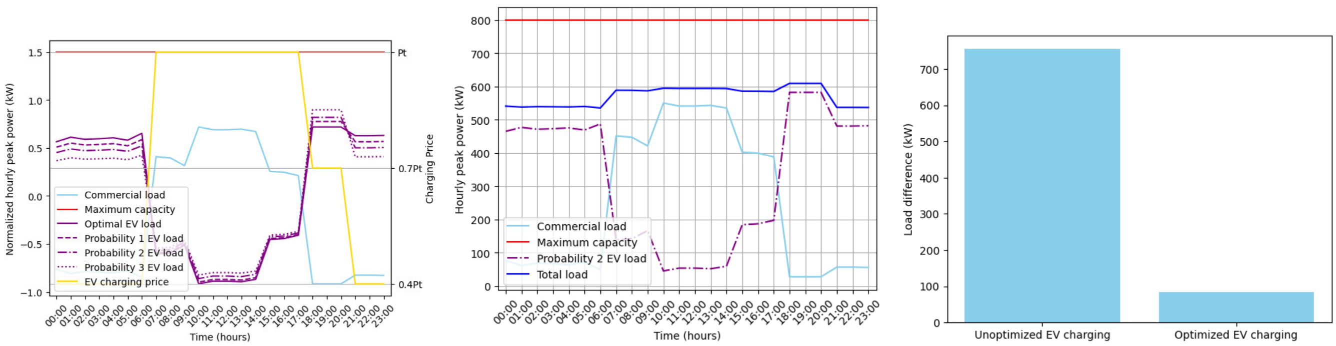
In comparison to Figure 6e, Figure 4f shows better load distribution over the period of 24 hours, with peak-to-valley differences of 760.00 kW and 79.86 kW respectively. This improvement is shown by a bar chart in Figure 6f.

3) VARYING EV LOAD ANALYSIS

In cases when the EV load is significantly greater than or less than the conventional load, the charging price and the subsequent EV load follow the patterns shown in Figure 5. Figures 5a and 5b show the residential area distribution grid results when the EV load is 25% lower and when



(a) Normalized load, suitable pricing mechanism, and normalized possible EV load (b) Total load as a sum of conventional residential load and probability 2 EV load (c) Load difference between the peak and the trough in residential distribution network



(d) Normalized load, suitable pricing mechanism, and normalized possible EV load (e) Total load as a sum of conventional commercial load and probability 2 EV load (f) Load difference between the peak and the trough in commercial distribution network

FIGURE 6. An illustration peak shaving and valley filling in residential and commercial areas as a result of dynamic charging pricing strategy.

the EV load is 25% higher than the conventional load respectively.

Similarly, Figures 5c and 5d show the commercial area distribution grid results when the EV load is 25% lower and when the EV load is 25% higher than the conventional load respectively. It can be seen that the charging price is set in a manner that inspires the EV load to be complementary to the conventional load, thereby optimally utilizing the grid.

V. CONCLUSION AND FUTURE WORK

In this work, the framework to charge electric vehicles in a load-balancing manner between residential and commercial/industrial distribution networks is proposed. Based on the evidence that most electric vehicles are charged when the price of electricity is at its lowest value, we use the distribution network-specific load-based dynamic EV charging price to control where and when the EVs are charged. The communication procedure to make known to EV users the availability of charging slots and charging prices in different areas is proposed. The method is tested with EVs load that is equal to the conventional grid load, the EVs load that is 25% higher than the conventional grid load, and the EVs load that is 25% lower than the conventional load. The load is distributed in different EV charging probabilities determined based on the EV charging price.

The results show that the distribution network is likely to operate optimally when most of the EV users are attracted by the incentive to charge EVs at the most convenient place and time, determined by the best charging price at a given time. This work adds contribution to the optimal integration of EVs in the smart grid, with a focus on the EVs charging. The future work will explore the integration of EVs into the smart grid, considering both EV charging and discharging, all while incorporating the learning algorithms.

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