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Dynamic pricing strategy for electric vehicle charging stations to distribute the congestion and maximize the revenue

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ABSTRACT

Electric vehicle (EV) charging station (CS) congestion is highly dependent on the EV owner's behavior and their selected CS as charging choice. A fixed pricing strategy causes some CSs to be congested with EVs waiting in line to charge, while there are some other CSs with available electric plugs, which adversely affects both charging station operator (CSO) revenue and EV users' welfare. To solve this problem, this paper presents a dynamic pricing strategy aimed at conducting EVs from congested CSs to the uncongested ones through controlling the charging prices of CSs at different times. The problem is formulated as a scenario-based stochastic optimization with the objective of maximizing overall revenue of the CSO. Moreover, an attraction function model is developed to quantify the charging choice of the EV owners by considering the effective parameters of CSs in EV charging choice decisions. QGIS software is used in this work to formulate a realistic modeling for CS locations and EV routes to calculate the distances from EVs to CSs. Three scenarios are designed to evaluate the performance of the proposed framework and to compare the results with the fixed pricing approach. The results indicate that the proposed dynamic pricing strategy mitigates the congestion of CSs while facilitating an increased number of charged EVs up to 48% as well as increasing the overall revenue of the CSO.

1. Introduction

Nowadays, transportation electrification is welcomed by both consumers and governments due to lower fuel cost and supporting green energy resources. Electric vehicles (EVs) usage is growing rapidly because of remarkable advancement in EV manufacturing technology. Owing to the possibility of working in both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) modes of operation, EVs can be considered as flexible resources moving around the network from power systems operation perspective. High penetration level of the EVs affects the normal operation of the power grid, which may pose serious challenges to the distribution system operator (DSO) [1–3].

Charging management of the EVs distributed over the grid and charging stations (CSs) is one of the most demanding problems in power system studies [4,5]. For example, depending on the location of CSs, quantity and location of EVs, and at a specific time slot, let us consider a scenario where some CSs are congested with EV users waiting for charging while there are plenty of available charging plugs in the other CSs. This situation has adverse impacts on the load profile of the grid and decreases the charging station operator (CSO) profits through selling electricity to the EV users. In this case, the electricity price of the CS is the main variable that can attract EVs to the uncongested CSs. For this purpose, various dynamic charging pricing methods are proposed [6–9].

There are several works in the literature that study charging pricing strategy as competition between CSOs and model the problem using game theory frameworks [10–17]. The authors in [10] investigate the price competition among CSs with renewable power generators using the Stackelberg game method. The price elasticity of EVs, the effect of the distance between an EV and the CSs, and the impact of the number and type of charging outlets are considered in this work; however, this work does not consider a realistic model of EV routes to the CSs and calculates the distances according to a simple geometric model which affects the accuracy of the results. The work in [11] presents a strategic charging pricing scheme for CSOs based on a non-cooperative Stackelberg game framework. The Stackelberg equilibrium investigates the pricing competition among multiple CSOs while a soft actor-critic based multi-agent deep reinforcement learning algorithm is developed to solve the proposed equilibrium framework while considering privacy-conservation constraints among CSOs. Nevertheless, this work does not present a closed form expression to show how vehicles are attracted to the different CSs. The authors in [12] analyze price competition among CSs with service capacity constraints and use an ordinal potential

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Nomenclature

Abbreviations

CS	Charging station
CSO	Charging station operator
DSO	Distribution system operator
EV	Electric vehicle
$G2V$	Grid-to-vehicle
KKT	Karush-Kuhn–Tucker
PEV	Plug-in electric vehicles
$QGIS$	Quantum geographic information system
SOC	State of charge
$V2G$	Vehicle-to-grid

Parameters, Variables, and Indices

ω_r	he worst-case scenario in the ambiguity set
$\overline{Pr}$	Upper limit of the charging price
$\underline{Pr}$	Lower limit of the charging price
ATT_{ij}^t	Attraction of charging station i to EV customer j at time t
$C_{batt,k}$	Battery capacity of the EV connected to the plug k
d_{ij}^t	Distance from EV customer j to charging station i at time t
f	Total revenue of CSO over all time horizon under study
f_i^t	Revenue of the charging station i at time t
j	Index for EV customers
k	Index for charging plugs
l_A/l_B	Distance of centers A/B from the intermediate location
M	Total number of charging stations indexed by i
$N_{av,i}^t$	Number of available charging plugs in charging station i at time t
$N_{occ,i}^t$	Number of occupied plugs of charging station i at time t
P_i	Average charging power of charging station i
POP_A/POP_B	Populations of centers A/B
Pr_i^t	Charging price of charging station i at time t
S_i	Number of electric charging plugs in charging station i
$SOC_{end,k}$	SOC of the EV connected to the plug k at the end of charging
$SOC_{str,k}$	SOC of the EV connected to the plug k at the start of charging
T	Total number of time slots indexed by t
T_A/T_B	Trade from the intermediate location attracted by centers A/B
$t_{end,ik}$	Charging end time of EV connected to the plug k at charging station i
W	Ambiguity set of scenarios

game framework to investigate the structure of the competition. Moreover, they propose a decentralized algorithm to enable effective price coordination to achieve equilibrium with maximized social welfare; however, the price competition model in this work does not consider the charging plug capacity and charger types existing in the CS, which affects the competition between the CSs. The work in [13] proposes a non-cooperative game pricing strategy framework by the approach of profit-sharing and user equilibrium principles to maximize the social welfare of the electrified transportation system stakeholders consisting of electricity wholesalers, fast charging stations, and EV users, but this work also does not propose a closed form function to show how EVs select their desired CS for charging. The work in [14] is focused on the EV public charging market with heterogeneous CSs under the time-based billing model. In the proposed hierarchical game, each CS sets the charging price to maximize its own revenue first, then the EVs choose their desired CSs and determine the charging time; however, the power flow constraints, which affect the pricing strategy and relevant results, are not considered in this work. The work in [15] studies dynamic pricing policy for maximizing the long-term profits of CSOs using multi-agent reinforcement learning and Markov game to model the layer of CSOs as a competitive market. However, the proposed model does not reflect the impact of charging level and number of electric plugs in each CS, which regulates the competitive market. The work in [16] is focused on maximizing the sum of the revenues of all CSs managed by one corporation, assuming other corporations' pricing strategies are fixed. The EV charging and CS pricing problems in this work are modeled as a hierarchical Stackelberg game with the corporation at the upper layer as the leader and EV flows at the lower layer as followers. Nevertheless, a simple linear assumption for the queuing cost is considered in this work that does not reflect the realistic model of EV sections.

Moreover, there are multi-level optimization methods proposed in the literature aimed at solving competitive charging pricing problems [18–21]. The work in [18] pro-poses a tri-level pricing framework where CSs set charging prices at the upper level, EVs make route and charging options at the middle level, and the electricity price is cleared in the power distribution network at the lower level. Then, the single-level optimal pricing model is established with traffic flow assigned, power generation scheduled, and electricity price explicitly contained via Karush–Kuhn–Tucker (KKT) conditions. A tri-level optimization model is proposed in [19], where the upper and middle levels capture the profit maximization problems of this CS and its competitor respectively, while the lower level represents the optimal power flow problem of the distribution network. In addition, the authors in [20] propose a bi-level programming model where the upper level is the load management problem, and the lower level is the charging station selection problem for EVs. The optimal solution of the lower-level problem is a function in the charging price that is determined in the upper-level problem. Nevertheless, the multi-level formulation of the problem in these works increases the complexity of the model and needs further considerations to reformulate the problem into a single level to overcome the computational challenges.

There are also other works aimed at optimizing the EV charging pricing problem as well as other technical factors. The work in [22] designs an optimal pricing scheme to minimize the service dropping rate of the charging station considering dual-mode charging station. Proposed pricing scheme minimizes the number of EVs that leave the charging station without being charged. Although this work improves the service quality, it does not optimize the queue length and total profit of CSs. A stochastic scheduling framework embedded with an incentive charging strategy for EVs is proposed in [23], in which DSO combines the scheduling of the power grid and EV charging by flexible price approaches to contribute to system operation, but this work does not propose a detailed model on EV and CS location and distance calculation, which highly impacts the selected CS by EVs. Moreover, a price-based transfer model is proposed to describe the correlation between charging price and EV transfer. The work in [24] classifies EVs into four categories according to distinct driving characteristics and charging requirements and then, determines optimum charging price and energy management of EV parking lots by considering price elasticity of EV charging demand. However, this work does not consider the effective parameters in the price elasticity model of EVs to reflect how EVs are guided toward the CSs. The authors in [25] proposed a smart dynamic pricing approach based on a fuzzy logic controller based decision-making structure for EV charging in a distribution system; however, the proposed algorithm does not reflect the effective parameters in EV charging process like location, number of plugs, and rated power of the chargers for CSs. The presented work in [26] considers uncertainties related to the charging demand volatility, inherent intermittency of renewable energy generation, and wholesale electricity price fluctuation within the stochastic dynamic pricing for EV charging service providers, but this work does not provide a model for CS selections by EVs that affects the EV charging problem. The authors in [27] present a new coordinated dynamic pricing model to reduce the overlaps between residential and CS loads by inspiring the temporal Plug-in electric vehicles (PEVs) load shifting during evening peak load hours. The idea in this work is to dynamically adjust the price incentives to drift PEVs toward less underutilized CSs. Although the proposed method improves the total load profile during the whole day by guiding EVs toward the uncongested CSs, the solution does not necessarily maximize the revenue of the CSs. The work in [28] studies the travel patterns of electric vehicles to predict the controllable capacity of electric vehicles. Then, the charging preferences of different types of users are studied and a pricing strategy is developed, which accounts for the dispatching requirements of the microgrid and dispatch of electric vehicle charging load based on price signals. Modeling the EV charging problem with focus on EV types and their status, instead of considering important parameters from power system perspective, gives a micro understanding of the problem with lots of variables and uncertainties that reduces the accuracy of the results. An online pricing strategy is established in [29] upon a reward-based model to prevent network instability and power outages. The utility in this work provides incentives to the charging stations for their contributions in the EVs charging load shifting. Then, a constrained optimization problem is developed to minimize the total charging demand of the EVs during peak hours. This work presents an interesting solution to enhance the power system resiliency, but it is not necessarily the optimum solution from the revenue perspective.

In addition, the work in [30] proposes a dynamic pricing and control of a solar-powered EV CS though bi-level optimization approach, where pricing tariffs ensure an economic and price responsive operation, then EV charging schedules are computed for energy bidding capacity to provide balancing services. However, the decision making process of the EV users on the CS selection is not modeled in this work, which potentially impacts the proposed time-of-use (TOU) dynamic pricing scheme. The authors in [31] investigated the charging behavior of EVs according to the price signals to maintain grid balance. They used travel simulation to establish the relationship between travel demand and electricity prices. Nevertheless, the formulated optimization model in this work is only with the objective to minimize the grid loss and voltage drop. Although technical performance enhancement can be considered as an objective in the model, the main goal in the dynamic pricing problem is to maximize the revenue of the CS, which is not considered in this work. The work in [32] developed a genetic algorithm-based multi-objective optimization model to generate hourly dynamic TOU electricity tariffs and facilitate the decision making in load scheduling. However, the problem with this work is that it studies the pricing method for a single CS, while the dynamic pricing definitely impacts the decision of the EV users on the selected CS, but this aspect of the dynamic pricing method is not investigated in this work.

To address limitations related to the previous works in the literature, and with the purpose of maximizing the CSO revenue as well as a uniform distribution of EVs over CSs, a dynamic pricing strategy is developed in this work considering a detailed EV charging process modeling. Furthermore, the charging choice of EVs is modeled in this work mathematically using the important parameters such as location of EVs and CSs, number of charging plugs in each CS, and average charging power of CSs. The geographical information and measurement are accomplished using the quantum geographic information system (QGIS) to have a realistic modeling of distances incorporated in the charging process modding and dynamic pricing scheme.

The major contributions of this paper are as follows:

1. Development and all-inclusive formulation of an attraction function that explains the charging choice of EVs depending on the charging price of the CS, distance from EV to the CS, number of charging plugs in CS, and average charging power of the CS.
2. Formulation of the proposed dynamic pricing strategy in the form of a scenario-based stochastic optimization problem with the objective to direct EV owners from congested CSs toward the uncongested ones and consequently maximize the gross profit of all CSs.
3. Utilizing a realistic geographical model of CS locations using QGIS software and helpful tools to compute the fastest routes from EVs to CSs in order to form the distance matrix used in the charging process modeling and dynamic pricing scheme.

The reason for focus on the congestion of the CSs in this manuscript is that the congestion of the CSs directly represents the distribution of EVs between different CSs, which impacts the number of charging EVs, total sold energy, and consequently the CSO revenue. Furthermore, the waiting time of the EVs can be measured by monitoring the congestion of the CSs and thereby enhancing the EV owners satisfaction through a more uniform distribution of EVs among CSs by the proposed dynamic pricing strategy.

In addition, Table 1 compares the pricing strategy, objectives, optimization method, and the technical considerations in this work with the most relevant previous works in the literature. According to the table, the online pricing strategy is proposed in [29], which can potentially cause inconvenience to the EV users in terms of frequent price updates. On the other hand, TOU pricing in [28,32] with hourly or three-level price update cannot fully utilize the advantage of dynamic pricing to maximize the CSO revenue. Therefore, the dynamic pricing with 5-minutes intervals is applied in this work to efficiently update the charging prices while considering the EV users' satisfaction. Moreover, the dynamic pricing problem is formulated as a scenario-based stochastic optimization program in this work to accurately account for the uncertainty of the EV load and their individual locations. The rest of the paper is structured as follows: Section 2 elaborates on the system model that comprises EV charging process modeling, attraction function to show how EV users select the desired CS for charging, and relevant assumptions. Section 3 proposes the dynamic pricing strategy with formulation in the form of the scenario-based stochastic optimization problem. Afterwards, performance evaluation of the developed pricing strategy and related simulation results are discussed in Section 4. Finally, Section 5 puts forward relevant conclusions of the work.

2. EV charging system model

This section elaborates on the proposed modeling of the EV charging system used in this study. Assumptions on how and when EVs select their desired CS to charge are explained. Attraction of a CS to the EVs is formulated and coverage zone of CSs is defined. Then, EV charging process and distribution of EVs between CSs are modeled.

2.1. Assumptions

There are several influence factors identified from studying behavioral attributes of different kinds of people which affects EV charging behavior. These factors are roughly divided into socio-demographic attributes and alternative attributes i.e., scenario factors [33]. The socio-demographic factors have been extensively investigated by some other prior works in the literature [34–38]. Different travelers may

Table 1
Comparison of the proposed dynamic pricing strategy with the previous works in the literature.

Work	Pricing strategy	Objective(s)	Optimization method	Technical considerations
[26]	Stochastic dynamic pricing	Max profit Max customer satisfaction Min the impact on the grid	Stochastic dynamic programming (SDP)	Active and reactive power flow
[27]	Coordinated dynamic Pricing	Min the overlap between the EV load and residential load	Rule-based heuristic	Temporal EV load shifting
[28]	Dynamic TOU pricing	Min total charging costs of EV users	Linear programming (LP)	EV travel patterns User satisfaction degree
[29]	Online pricing	Min the EVs' charging loads at peak hours	Online reinforcement learning	Load shifting
[32]	Hourly dynamic TOU tariff	Min electricity cost Min peak-to-valley difference	Genetic algorithm	Price elasticity of demand Demand response program
This work	Dynamic pricing with 5-min frequency	Maximize the CSO revenue	Scenario-based stochastic optimization	Modeling EV decision on the CS selection Modeling EV charging process Geographical model of EV distances to CSs

make different charging choices when facing the same situation, and socio-demographic variables are considered to reflect the changes of the travelers in behavioral studies. Strong relationships exist among socio-demographics, activity engagement, and travel behavior [34]. The travel patterns of low-income people and high-income people are significantly different, as well as age, gender, driving experience, and education level. In addition, the work in [35] considers the heterogeneity of individuals and take these influencing factors as the latent variables that are unique to individuals, such as risk aversion attitude and positive vehicle maintenance attitude. The heterogeneity of individuals is included in this work by studying the socioeconomic characteristics of users, measurement of individual attitudes and a discrete choice experiment through the conducted face-to-face survey. The work in [36] studies a comparative and mixed methods assessment of the influence of gender, education, occupation, age, and household size on the importance of EV charging time, EV public chargers, and fuel economy preferences, drawing primarily on a survey across the Nordic region. The authors in [37] investigated the importance of socio-demographic attributes, geographic conditions, car interest, personal and social norms, and environmental concerns. Logistic regression analyses on the collected data through survey show how age, education level, and more importantly the individual's personal norms impact the EV travel behavior. Additionally, the work in [38] establishes the relationship between the public charging infrastructure and 21 socio-demographic, technical, and economic factors using mixed-effect regression method and according to the governmental sources and press articles data.

On the other hand, scenario factors include the battery's state of charge (SOC), charging cost, range anxiety, etc. SOC reflects the vehicle's remaining energy and is considered to be one of the most important factors. Price is another critical factor that EV travelers are concerned about. In normal situation, people prefer a low price [39]; however, some EV owners are time-conscious who are willing to pay more and save time by visiting the uncongested CSs. This paper is aimed at specifically developing a quantitative charging behavior model, which includes the effective parameters of CSs in EVs charging choice, as discussed in the next section.

2.2. CS attraction function and coverage zone

In order to encourage EVs to use the more uncongested CSs for charging and to consequently increase the CSOs revenue, it is necessary to have a proper understanding of how EVs individually select their target CS. From Reilly's law of retail gravity [40], two cities attract retail trade from any intermediate city or town in the vicinity of the breaking point, approximately in direct proportion to the population of the two cities and in inverse proportion to the square of the distances from these two cities to the intermediate town. This idea can be quantified through the following function:

$$\frac{T_A}{T_B} = \frac{POP_A}{POP_B}\left(\frac{l_B}{l_A}\right)^2 \tag{1}$$

where T_A and T_B represent the trade from the intermediate location attracted by centers A and B, POP_A and POP_B are populations of centers, and l_A and l_B represent distance of centers A and B from the intermediate location. In this modeling, attraction of a specific center depends on its population and distance from the intermediate location. By applying Reilly's law of retail gravity to the EV charging context, CSs can be considered as the centers and EVs are the customers located in the intermediate points. Population of the centers in (1) should be replaced by the parameters of EV charging context which affects the decision of the EV owners in choosing their desired CS. To have a proper consideration of effective parameters in attraction of a CS, the basic attraction function which will be used for the proposed dynamic pricing framework in this work is formulated in a modified form as follows.

$$ATT_{ij}^t = \frac{S_i\ P_i}{Pr_i^t\left(d_{ij}^t\right)^2} \tag{2}$$

This equation represents ATT_{ij}^t, which is the attraction of CS_i to the jth EV at time t. S_i in this equation is the total number of electric charging plugs in the CS_i, P_i is the rating power of the chargers in CS_i corresponding to the charging level of the CS, Pr_i^t is the electricity price of CS_i at time slot t, and d_{ij}^t is the distance between the jth EV and CS_i at time t. Here, it is assumed that the CS parameters in (2) are shared with the EV users through navigation systems, mobile apps, or online maps. In addition, it is assumed in this study that the CS is the final destination of the EV at the time of decision-making, and no changes are made in the CS selection in the proposed model after an EV user selects a CS candidate. Also, the time and energy cost related to the traveling from the current location to the selected CS is reflected in the attraction function by parameter d_{ij}^t, which is the distance between the jth EV and CS_i at time t. This distance is calculated by the QGIS that provides a realistic distance according to the fastest realistic routes rather than considering the direct distance between the two points which may not be a realistic estimate. The parameters included in the

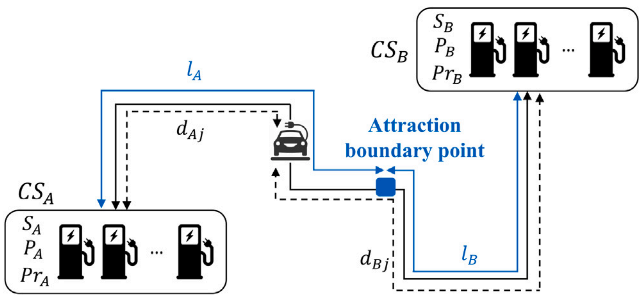

Fig. 1. Competition of two CSs to attract an EV for charging.

attraction function in (2) are aligned with the EV user's welfare, while a higher rating power of the charger corresponds to the lower charging time and a higher number of charging plugs in the CS introduces higher chance of achieving a faster charging. Competition between two CSs to attract an EV is illustrated in Fig. 1. The attraction boundary point in this figure is the intermediate location where the attractions of the two CSs to the EV at this point are equal. The boundary point can be calculated by (3) as presented below:

$$l_A = \frac{l_A + l_B}{1 + \sqrt{\frac{S_B\, P_B\, Pr_A}{S_A\, P_A\, Pr_B}}} \tag{3}$$

where l_A and l_B are the distance from the attraction boundary point to the CS_A and CS_B, respectively. The boundary points determine the coverage zone of CSs. Larger coverage zone of CS increases the chance of CS to attract more EVs. Considering the fixed number of charging plugs and charger rating power for CSs, Eq. (3) demonstrates that the coverage zone of CS depends on the electricity price.

In a specific scenario in Section 5, it is assumed that the CSs are equipped with an online crowd meter that means the EV owners can check the availability of the electric plugs at different CSs and make decisions based on this additional information. In this case, proposed attraction function is modified as expressed below:

$$ATT_{ij}^{t} = \frac{S_i\, P_i\, N_{av,i}^{t}}{Pr_i^t \left(d_{ij}^t\right)^2} \tag{4}$$

where $N_{av,i}^{t}$ is the number of available charging plugs of CS_i at time t. Moreover, the CS boundary point in this case is calculated by

$$l_A = \frac{l_A + l_B}{1 + \sqrt{\frac{S_B\, P_B\, N_{av,B}\, Pr_A}{S_A\, P_A\, N_{av,A}\, Pr_B}}} \tag{5}$$

2.3. EV charging process model

Charging process modeling of the EVs during the time horizon under study is proposed in this section as presented in Fig. 2. The model starts with initializing CSs data, status of plugs, maximum acceptable waiting time, and time horizon under study. Then, all the plugs in CSs are first checked at the current time slot t^* to see if any EV has completed charging. This is done by comparing the calculated charging end time ($t_{end,ik}$) in (6) with the current time slot (t^*) for all the plugs indexed by k at all the CSs indexed by i.

$$t_{end,ik} = \frac{(SOC_{end,k} - SOC_{str,k}) * C_{batt,k}}{P_i} \tag{6}$$

In this equation, $SOC_{end,k}$ and $SOC_{str,k}$ represent the end and start SOC of the EV connected in the charging plug k, respectively. $C_{batt,k}$ is the capacity of the EV battery, and P_i is the average charging power of the ith CS. If the EV is charged completely, the corresponding plug status will be updated to "available". Next, the model checks if any EV needs to be charged at the current time t. The arriving EVs choose

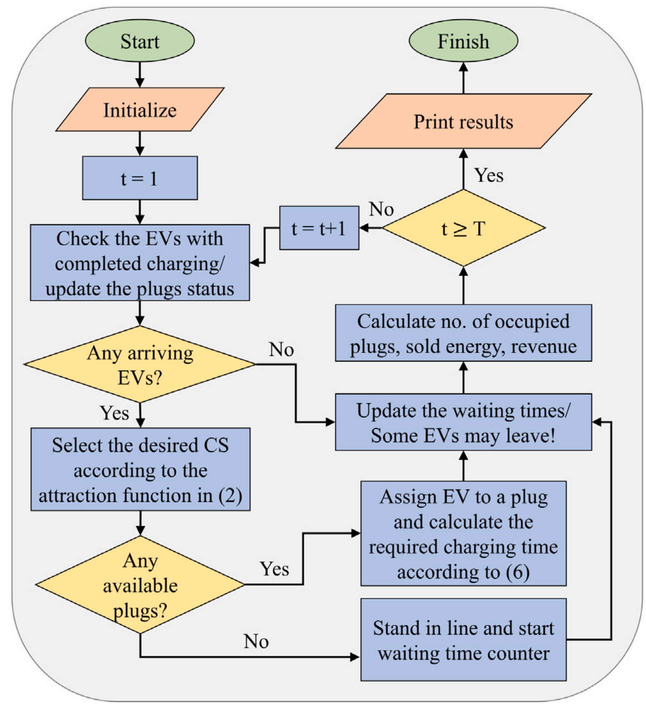

Fig. 2. EV charging process modeling flowchart.

their desired CS according to the attraction function in (2) and select the CS with the highest attraction as their charging choice. If there is any available plug at the desired CS, the EV is assigned to a plug and the charging end time is calculated by (6); otherwise, the EV should wait in line for an occupied plug to be available. If there is not any available plug until the maximum waiting time $t_{w,max}$, the EV leaves the CS.

At the end of each time slot, the total sold energy and corresponding CSO revenue is calculated based on the number of occupied plugs, electricity price, and charging power level of the CSs. The process iterates for all the time slots under study, and finally the overall results are published.

The dynamic pricing strategy formulated in Section 3 is aimed at managing the EV routes with the presented charging process to minimize the number of EVs waiting at the CSs and conduct EVs from congested CSs toward the uncongested ones, which eventually increases the total revenue of CSO.

3. Dynamic pricing strategy to maximize total CSO revenue

With the goal of utilizing potential flexibility of the charging price of CSs, this section presents the dynamic pricing strategy formulation, developed objective function, applied optimization method, and relevant constraints. The main purpose is to optimally control the charging price of CSs to encourage EV owners to use uncongested CSs, which increases both EV customers' welfare by minimizing the waiting time and CSO total revenue by maximizing total sold energy. This study considers the case that all the CSs are governed by one single entity, say a CSO and the objective is to maximize the net profit sum obtained from all the CSs under that CSO. So, we have a single player and there is not any competition; hence, the Nash equilibrium is not applicable in the considered study. Due to the random nature of EV models, start and end SOC, arrival times, and location of EVs when they want to choose the target CS to charge, the problem is formulated by a scenario-based stochastic optimization method, where the worst-case scenario is considered in each case study in order to have a conservative approach toward the problem and results. This consideration leads to

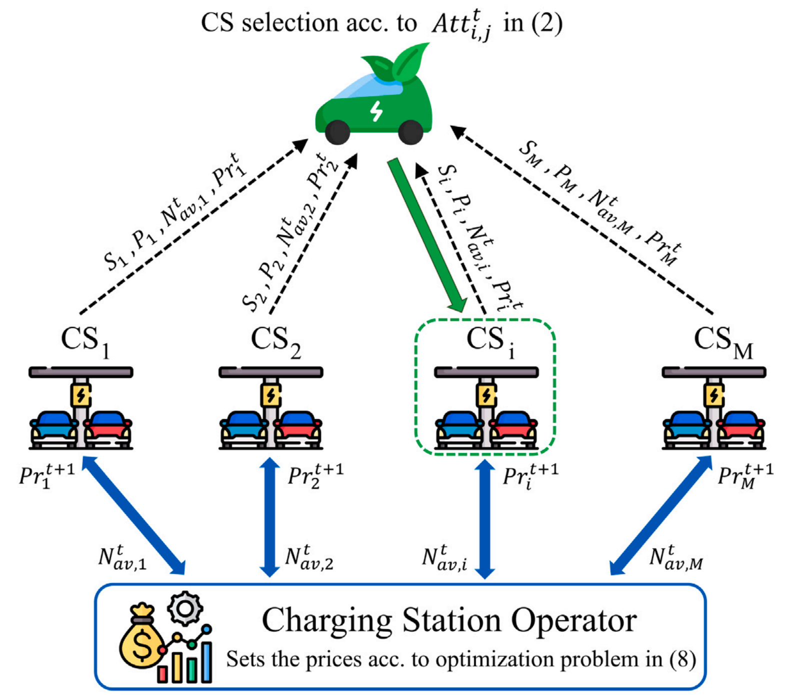

Fig. 3. Communications in the proposed dynamic pricing strategy.

robust scenario-based results where the minimum performance of the proposed dynamic pricing strategy corresponding to the worst scenario is compared with the fixed pricing strategy. Also, it is possible to use a probability distribution for scenario selection; however, due to high uncertainties related to the EVs arrival time, start and end SOC, and EV battery capacity, it is not guaranteed to find such an accurate distribution. Therefore, a robust scenario-based approach is adopted in this work.

Fig. 3 shows the communications between CSs, EVs, and CSO within the dynamic pricing strategy. According to this figure, CSs share their information on the charging power, total number of charging plugs, number of available charging plugs at time t, and the charging price at time t with the EV owners. EV owners select their desired CS according to the developed attraction function in (2). On the other hand, CSO monitors the occupancy of the CSs at time t and sets the charging prices for the following time slot ($Pr_i^{t+1} \quad \forall i$) accordingly in an optimal fashion to maximize the revenue and increase the EV owners' satisfaction by reducing their waiting time and offering cheaper charging prices.

3.1. Scenario-based stochastic optimization for dynamic pricing strategy

EVs are attracted to the CSs according to the CS parameters proposed in attraction function in (2) and based on the EV charging process model, presented in Section 2.3. Here, the objective is to determine the optimum set of CS charging prices (Pr_i^t) that leads to the CSs to support the maximum EVs during the whole time under study. In other words, dynamic pricing of CS changes the attraction of CSs over time so that EVs are encouraged to use cheaper CSs, which are probably uncongested CSs as well; hence, CSO can sell more electricity and its revenue is maximized. The revenue of CS_i at time t is calculated based on the electricity price, number of occupied charging plugs, and the charging power, as expressed in (7), and the objective function of the scenario-based stochastic optimization problem is defined in (8) for all CSs and time slots accordingly as follows.

$$f_i^t = Pr_i^t \, N_{occ,i}^t \, P_i \tag{7}$$

$$\max_{Pr_i^t} \quad f = \sum_{t=1}^{T} \sum_{i=1}^{M} Pr_i^{t,\omega_r} \, N_{occ,i}^{t,\omega_r} \, P_i \quad \forall \omega_r \in W \tag{8}$$

where ω_r is the worst-case scenario existing in the ambiguity set W. The objective function in (8) is subject to the EV charging process model presented Section 2.3 and charging price limits as follows.

$$\underline{Pr} \le Pr_i^t \le \overline{Pr} \quad \forall i, t \tag{9}$$

The minimum charging price is typically set to cover the costs of providing the service including electricity cost, infrastructure cost, maintenance cost, taxes, and profits. On the other hand, the maximum charging price is mainly determined by electricity market competition and consumer demand. In some cases, market regulators may set a cap on charging prices to safeguard consumers against price gouging.

3.2. Optimization method

The constrained optimization problem in (8) is formulated as follows by replacing the variables Pr_i^t with x.

$$\min_x -f(x) \tag{10a}$$

$$h(x) = 0 \tag{10b}$$

$$g(x) \le 0 \tag{10c}$$

where f, h, and g are twice continuously differentiable functions. Using an interior method, the nonlinear program in (10) can be replaced by a sequence of barrier subproblems in the form of (11) as follows.

$$\min_z \varphi_\mu(z) \equiv -f(x) + \mu \sum_{i=1}^{m} \ln s_i \tag{11a}$$

$$h(x) = 0 \tag{11b}$$

$$g(x) + s = 0 \tag{11c}$$

Here, $s > 0$ is a vector of slack variables, $z = (x, s)$, and $\mu > 0$ is the barrier parameter. The Lagrangian function associated with (11) is defined by

$$\mathcal{L}(z, \lambda; \mu) = \varphi_\mu(z) + \lambda_h^T \, h(x) + \lambda_g^T \, (g(x) + s) \tag{12}$$

where λ_h and λ_g are Lagrange multipliers and $\lambda = (\lambda_h, \lambda_g)$. The first-order optimality conditions for the barrier problem in (13) can be

Table 2
Pricing Strategies Under Study.

Case number	Pricing strategy
I	Fixed pricing
II	Peak and off-peak pricing
III	Proposed dynamic pricing framework
IV	Proposed dynamic pricing + CSs equipped with crowd meter

expressed by

$$\begin{bmatrix} \nabla f(x) + A_h(x)^T\, \lambda_h + A_g(x)\, \lambda_g \\ S\Lambda_g e - \mu e \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{13}$$

together with (11b), (11c) and restriction that s and λ_g be nonnegative. Here S and Λ_g denote diagonal matrices with the entries given by vectors s and λ_g, respectively, and A_h, A_g are the Jacobian matrices of h and g.

Applying Newton's method to the system (13), (11b), and (11c), from the current iterate (z, λ) results in the primal–dual system presented below:

$$\begin{bmatrix} W(z, \lambda; \mu) & A(x)^T \\ A(x) & 0 \end{bmatrix} \begin{bmatrix} d_z \\ d_\lambda \end{bmatrix} = - \begin{bmatrix} \nabla_z\, \mathcal{L}(z, \lambda; \mu) \\ c(z) \end{bmatrix} \tag{14}$$

where

$$d_z = \begin{bmatrix} d_x \\ d_s \end{bmatrix}, \quad d_\lambda = \begin{bmatrix} d_h \\ d_g \end{bmatrix}, \quad c(z) = \begin{bmatrix} h(x) \\ g(x) + s \end{bmatrix} \tag{15}$$

$$A(x) = \begin{bmatrix} A_h(x) & 0 \\ A_g(x) & I \end{bmatrix} \tag{16a}$$

$$W(z, \lambda; \mu) = \begin{bmatrix} \nabla^2_{xx}\, \mathcal{L}(z, \lambda; \mu) & 0 \\ 0 & S^{-1}\, \Lambda_g \end{bmatrix} \tag{16b}$$

The new iterate is given below using step lengths α_z and α_λ.

$$z^+ = z + \alpha_z d_z, \quad \lambda^+ = \lambda + \alpha_\lambda d_\lambda \tag{17}$$

To validate the efficacy of the proposed dynamic pricing scheme, performance evaluation is presented in the next section that includes the case study, simulation results, and related discussion.

4. Performance evaluation of developed dynamic pricing strategy

This section presents the case studies to validate the efficacy of the proposed dynamic pricing strategy. In addition, a realistic model of CS locations and EV routings is presented using geographical modeling tools. Further, simulation results and relevant discussion are presented.

4.1. Scenarios and simulation setting

To assess the performance of the proposed CS dynamic pricing strategy, four pricing strategies are studied in this work according to Table 2. Case I introduces a fixed pricing strategy with the electricity price equal to the average charging price of the dynamic pricing in case III. Case II represents the peak and off-peak pricing as the most fundamental dynamic pricing method, which shows how the EV users respond to the changes in charging prices, but in only two price levels defined according to the EV charging load demand. Case III investigates the basic form of the developed dynamic pricing strategy where the charging price of CSs are varying dynamically over the time with the objective of maximizing total revenue of the CSO, as presented in (8). Finally, case IV considers an additional assumption of the CSs equipped with an online crowd meter, which affects the attraction function of the CS and consequently the decision of the EV users on the selected CS to visit, as expressed in (4).

Another impactful factor in the dynamic charging pricing problem is the difference between weekday and holidays. It is worth mentioning that the primary component that the holidays/weekdays related test-case distinctively takes care of is the aspect of different EV charging demand profiles in the analysis, which would not alter any fundamental part of the CS selection strategy and the charging process model developed in Section 2. Furthermore, the peak and off-peak pricing strategy defined as case II investigates the similar impact as the holidays/weekdays analysis has on the EV charging demand profile and consequently on the charging pricing, number of charged EVs, total sold energy, and finally total revenue of the CSO.

The EV charging process model is simulated according to the flowchart presented in Fig. 2 over a 1-day time horizon with 5-minute steps corresponding to 288 time slots. The frequently variations of charging price will increase the operation difficulty of the CS operator and also may cause inconvenience to the EV owners. On the other hand, lower frequency of the price updating prevents the CS operator to take advantage of the dynamic pricing strategy fully to maximize the revenue by more uniform distribution of the EVs among different CSs. In this study, the frequency of the price updating (i.e., every 5 min) is selected according to the farthest possible CS selection of the area under study. It means that if an EV selects the farthest CS which has the highest attraction (through offering very low charging price, high charging power, or a greater number of available charging plugs), the EV selects that corresponding location as the final destination without any change in price on the way. Therefore, the time interval of price updates is selected based on the maximum time required for an EV to travel to the farthest CS with higher attraction, which is 5 min in this case study. Once a CS selection is made, the choice is locked in and cannot be altered along the way.

Number of 12 CS equipped with Level-2 chargers with an average charging power of 7.2 kW located in Tempe, Arizona, USA is considered with the number of charging plugs presented in [41]. Further, to investigate the impact of charging level in this study, 4 more DC-fast CSs with the average charging power of 50 kW are included. To have a realistic understanding of CS locations and EV routes, it is necessary to use a geographical tool. QGIS software with high capabilities is used for this purpose. Based on the location of the CSs on the map and according to the number and random location of the EVs at time t, the fastest routes of EVs to the CSs are obtained, as shown in Fig. 4, and finally distance matrix D^t is formed that includes the distance of individual EVs to each CS. Then, these distances are used to calculate the attraction of each CS to the EV users according to the developed model in (2), which subsequently is used in the charging process model and developed dynamic pricing framework. The EVs demand profile pattern used in this work is according to the realistic profile presented in [42], as illustrated in Fig. 5. According to the EV demand profile, hours 8 to 15 are assigned to the peak hours and the other hours are considered as the off-peak hours in the peak and off-peak pricing strategy defined in case II. Furthermore, To have a realistic modeling of EV battery capacities, ten common EV models along with their battery capacity and corresponding full charging time for level-2 and DC-fast charging systems are presented in Table 3.

Incorporating traffic situations into the dynamic pricing strategy offers the potential for more accurate estimations of charging demand and user behavior, but it comes with several challenges. The complexity of the model increases significantly due to the need to account for various factors influencing traffic conditions, such as time of day, weather, and special events. Obtaining and managing the extensive data required for accurate modeling can be resource-intensive, and frequent updates may strain computational resources, which is a challenge in real-time implementation. Additionally, uncertainty in traffic patterns poses a challenge, as unexpected events can disrupt travel times and route choices. Implementing dynamic pricing based on traffic conditions may also raise regulatory, ethical, and competitive concerns, necessitating careful consideration of the trade-offs involved in adopting such a pricing strategy.

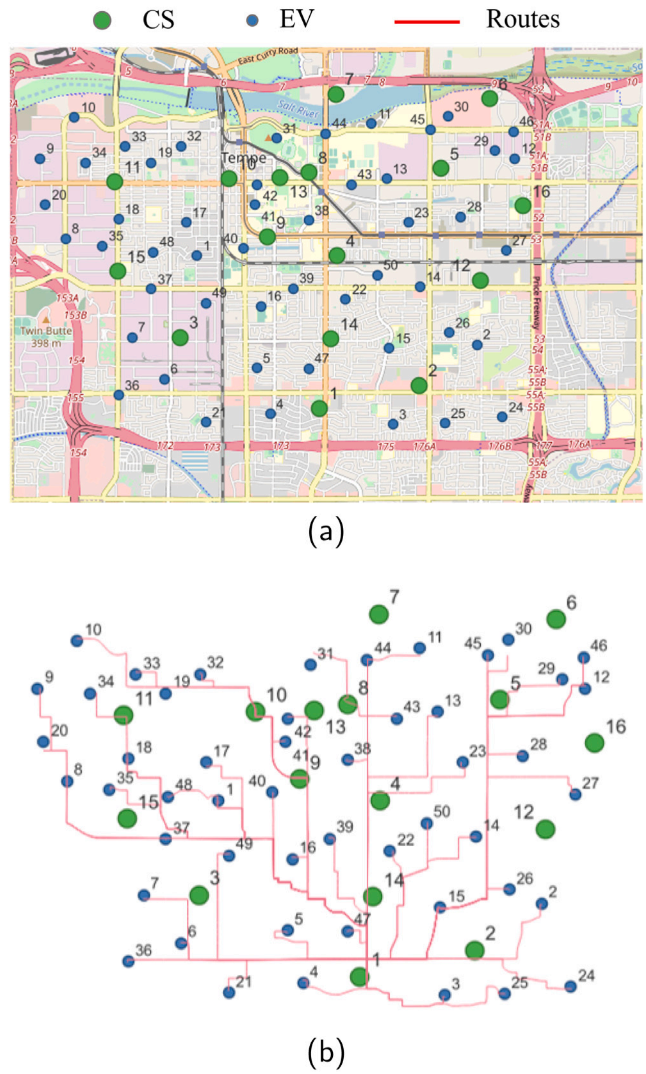

Fig. 4. CS locations and EV routes modeling using QGIS; (a) CS and EV locations at a specific time; (b) fastest EV routes to CS_1 that is used to form the distance matrix.

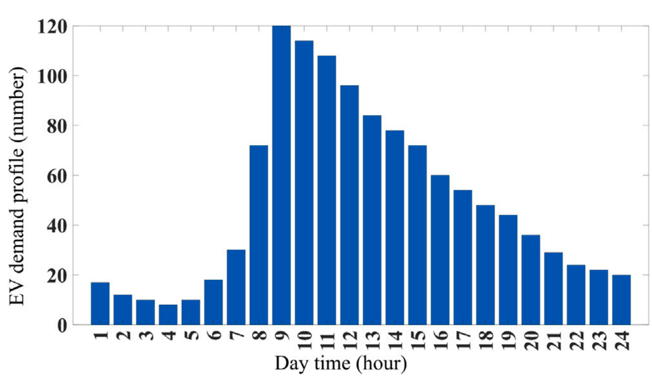

Fig. 5. EVs demand profile pattern.

4.2. Results and discussion

To evaluate the performance of the proposed dynamic pricing strategy, detailed results and discussion are presented in this section. Table 4 shows the overall simulation results of the four pricing strategies. In the fixed pricing scenario (case I), 758 EVs are charged over all time slots that leads to the total revenue of $2,061. The charging price in case I is fixed for all CSs and during all time slots. In case II, the number of charged EVs is increased to 864, which results in 14% more sold energy in comparison with the case I. The CSO revenue in this case is $2,371, and the average waiting time of the EVs is reduced to 15 min that is 4 min less the case I. It is observed that the proposed dynamic pricing method in case III can increase the number of charged EVs to 1,046 through changing the charging price of the CSs and consequently manipulating the attractions of the CSs to the customers to encourage them to use the uncongested CSs. The total sold energy is increased from 23.56 MWh in case II to 28.64 MWh in case III corresponding to the total revenue of $2,917. Additionally, case IV is defined such that CSs share more information with EV users through the online crowd meter that shows the online number of available electric plugs at each CS. This additional information causes more EVs to visit the uncongested CSs and increases the number of charged EVs to 1,128 corresponding to the 29.57 MWh sold energy and $3,069 revenue for the CSO.

Table 3
EV Models Characteristics.

No.	EV Model	Capacity (kWh)	Level-2 full charging time (h)	DC-fast full charging time (h)
1	Tesla Model S	100	13.8	2
2	Tesla Model X	100	13.8	2
3	Tesla Model 3	50	6.9	1
4	Tesla Model Y	68	9.4	1.36
5	Chevrolet Bolt EV	65	9	1.3
6	Nissan Leaf	40	5.5	0.8
7	Ford Mach-E	70	9.7	1.4
8	Audi e-tron	95	13.2	1.9
9	Porsche Taycan	79	10.9	1.58
10	Hyundai Kona	64	8.9	1.28

From the CS revenue perspective, the high attraction CSs (e.g., CSs equipped with DC fast chargers or CSs with a high number of charging plugs) can keep a high charging price with fully occupied charging plugs to maximize the revenue, while the other CSs need to reduce their charging price to attract more EVs. The added revenue in this case is due to the increased number of charged EVs, as presented in Table 4. This leads to both more sold energy and more revenue for the CS operator and enhanced satisfaction of the EV owners resulted by lower waiting times.

The other benefit of the proposed dynamic pricing strategy is enhanced satisfaction of EV owners through reducing the average waiting times resulted by distributing the congestion of the CSs, as illustrated in Table 4. A maximum waiting time is considered in the EV charging process modeling that shows EV owners will leave the CS after this waiting time. The number of EVs that leave the CSs after the defined maximum waiting time reflects the customer satisfaction level of the charging systems infrastructure. From Table 4, the average waiting time of the EVs is reduced from 19 min for case I to 9 min for case IV, reflecting the great satisfaction of EV owners thanks to the proposed dynamic pricing strategy. Furthermore, Fig. 6 shows the number of EVs left the CSs during the peak time slots between t = 84 to t = 180 corresponding to the hours 8 to 15. It is observed that the proposed dynamic pricing strategy in cases III and IV can significantly reduce the number of departed EVs by changing the charging prices and consequently distributing the EVs toward the uncongested centers.

The visual distribution of EVs at the specific time slot t = 137 for different case studies is illustrated in Fig. 7, which demonstrates the impact of the proposed dynamic pricing strategy in terms of increased number of charging EVs and a more uniform distribution of EVs among different CSs. This is a scaled figure where the bigger EV icon corresponds to a greater number of charging EVs at the relevant CS. Comparison of all cases gives the result that each case leads to an

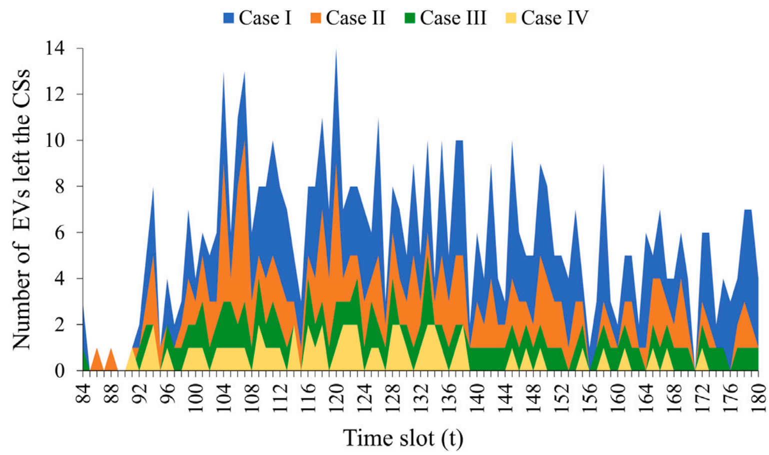

Fig. 6. Number of EVs departed the CSs after maximum waiting time during the peak load correspondent time slots.

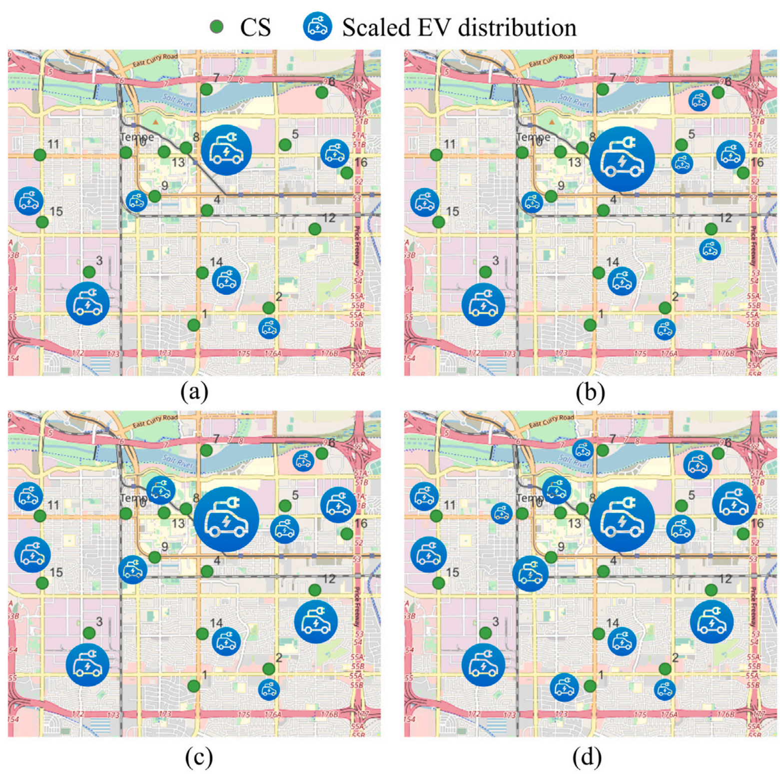

Fig. 7. Scaled distribution of charging EVs at t = 137 in different case studies: (a) Case I; (b) Case II; (c) Case III; (d) Case IV.

Table 4
Overall Simulation Results.

Case no.	No. of charged EVs	Waiting time (min)	Sold energy (MWh)	Revenue of the CSO ($)
I	758	19	20.61	2,061
II	864	15	23.56	2,371
III	1,046	11	28.64	2,917
IV	1,128	9	29.57	3,069

enhanced EV distribution and number of charging EVs than the previous case. The more uniform distribution of EVs in cases III and IV is achieved thanks to the proposed dynamic pricing strategy and changing the charging prices to conduct the EVs toward the uncongested CSs and thereby enhancing satisfaction level of EV owners by lower waiting times.

Moreover, Table 5 demonstrates details on the impact of dynamic pricing method on distribution of EVs between CSs. In case III, CS charging prices are in the range of 5 to 15 $¢/kWh$ at t = 137 while high-attraction CSs corresponding to the higher number of charging plugs and higher average charging power of chargers have the highest price that increases the revenue of the CSO. On the other hand, keeping the price at a higher level decreases the attraction of the CS to EVs that decide to charge at the next time slots, as observed for the CSs 12 and 13. Further, comparing the prices at t = 137 and t = 138 shows that CSs 1, 2, 6, 8, 9, 10, and 11 have attracted more EVs by reducing their electricity price and consequently increasing the attractiveness of their service. Moreover, CSs 14, 15, and 16 that provide the DC-fast charging service with lower charging times are among high-attraction CSs that can keep higher prices while the EV users are still satisfied and select these centers as their charging choice. Regarding the case I, because of the fixed pricing approach, the changes in attractiveness of the CSs

Table 5
Impact of Dynamic Pricing on Distribution of EVs.

CS no.	Case III				Case I	
	Pr_i^{137} (¢/kWh)	$N_{occ,i}^{137}$	Pr_i^{138} (¢/kWh)	$N_{occ,i}^{138}$	$N_{occ,i}^{137}$	$N_{occ,i}^{138}$
1	9.07	0	7.77	1	0	0
2	15	3	13.56	4	3	3
3	14.99	7	15.00	8	8	8
4	5.01	0	5.00	0	0	0
5	14.98	4	14.99	4	0	0
6	7.72	1	5.38	7	0	0
7	5.00	0	5.03	0	0	0
8	15	16	14.51	27	16	17
9	10.15	2	8.28	3	0	1
10	14.99	0	7.03	1	0	0
11	15.00	2	5.01	3	0	0
12	13.40	6	11.40	4	0	0
13	14.51	2	9.07	1	0	0
14	15.00	2	15.00	2	2	2
15	15.00	4	15.00	4	3	3
16	15.00	3	15.00	5	2	2

during the time are only due to the varying distances of the EVs to the CSs, which does not cause any remarkable change in the attraction of the CSs, so it is observed that the EVs are distributed between the same CSs at both time slots. In other words, EV owners do not see any benefit to visit the other centers because of the fixed pricing approach, which reduces both EV owners welfare and CSO revenue. Also, a more uniform distribution of the EVs resulted by dynamic pricing framework can be concluded from the total number of charged EVs at a specific time slot for each case; at $t = 137$ slot, 34 EVs are charged in all CSs while this number increases to 52 EVs in case III.

Fig. 8 represents the impact of dynamic pricing strategy in case III on competition between CSs to attract the EVs by comparing the CS coverage zones and their boundary points. It can be observed from Fig. 4 that CS_5 has 6 neighbors including CSs number 4, 6, 7, 8, 12, and 16. To have a better illustration, the boundary point (and consequently coverage zone) shifts between CS_5 and its neighboring CSs are shown in Fig. 8(a) in an hourly manner during the day and corresponding dynamic charging prices along with the EV charging load demand are illustrated in Fig. 8(b). For example, it is observed that the charging price of CS_6 at $h = 4$ is decreased, which increases the attraction and as a result the coverage zone of this CS is widened. This means that a greater number of EVs located in the routes between CS_5 and CS_6 during the $h = 4$ are willing to visit CS_6 for charging rather than CS_5 due to the higher price of CS_5. The similar results can be concluded during $h = 4$ for interactions between CS_5 and CS_{12}. The charging price for CS_{12} is reduced during this hour to attract more EVs. Also, it is observed from Fig. 8(a) that the impact of this price reduction is reflected in the distance from CS_{12} to the boundary point between CS_5 and CS_{12}. In this situation, more EVs located between CS_5 and CS_{12} are attracted by CS_{12} in comparison to the previous time slot due to the reduced charging price of this CS during the fourth hour.

Similarly, the impact of dynamic pricing strategy in case IV on the competition between CS_5 and its neighboring CSs to attract more EV users are illustrated in Fig. 9(a). Also, the dynamic charging prices during the day and the EV load demand are shown in Fig. 9(b). For instance, comparing the distance from CS_5 and CS_8 from the boundary point between these CSs gives the idea that CS_8 has a larger coverage zone rather than CS_5 all over the day. The reason is that CS_8 in this study has the greatest number of 32 charging plugs, which notably increases the attraction of this CS to the EV users according to the attraction function in (2). Therefore, this CS maintains a relatively high charging price during the day to result more revenue to the CSO; although it is observed that this CS has reduced its charging price in a few hours such as $h = 2$ and $h = 8$ to keep the attraction in a high level. The other CS that has a larger coverage zone than CS_5 during all

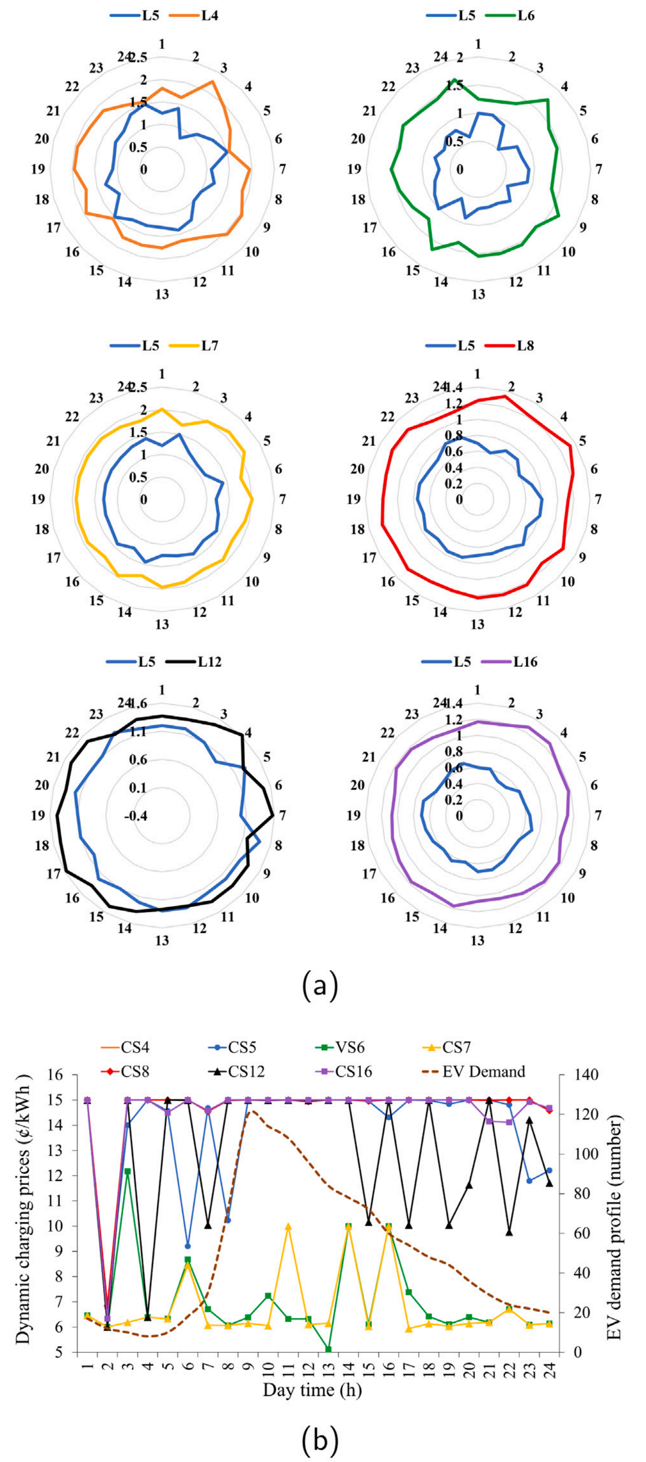

Fig. 8. Impact of dynamic pricing strategy in case III on CS boundary points; (a) variations in distance from the CS_5 to the boundary points respect to its neighboring CSs; (b) dynamic charging prices of CS_5 and its neighboring CSs along with the EV charging demand.

the hours is the CS_{16}. The reason for this observation is that the CS_{16} is equipped with the DC-fast chargers, which significantly reduces the charging time, and this is an attractive feature to the EV users; hence, this CS has a higher attraction, larger coverage zone, and consequently a longer distance to the boundary point in comparison with the CS_5 all over the day.

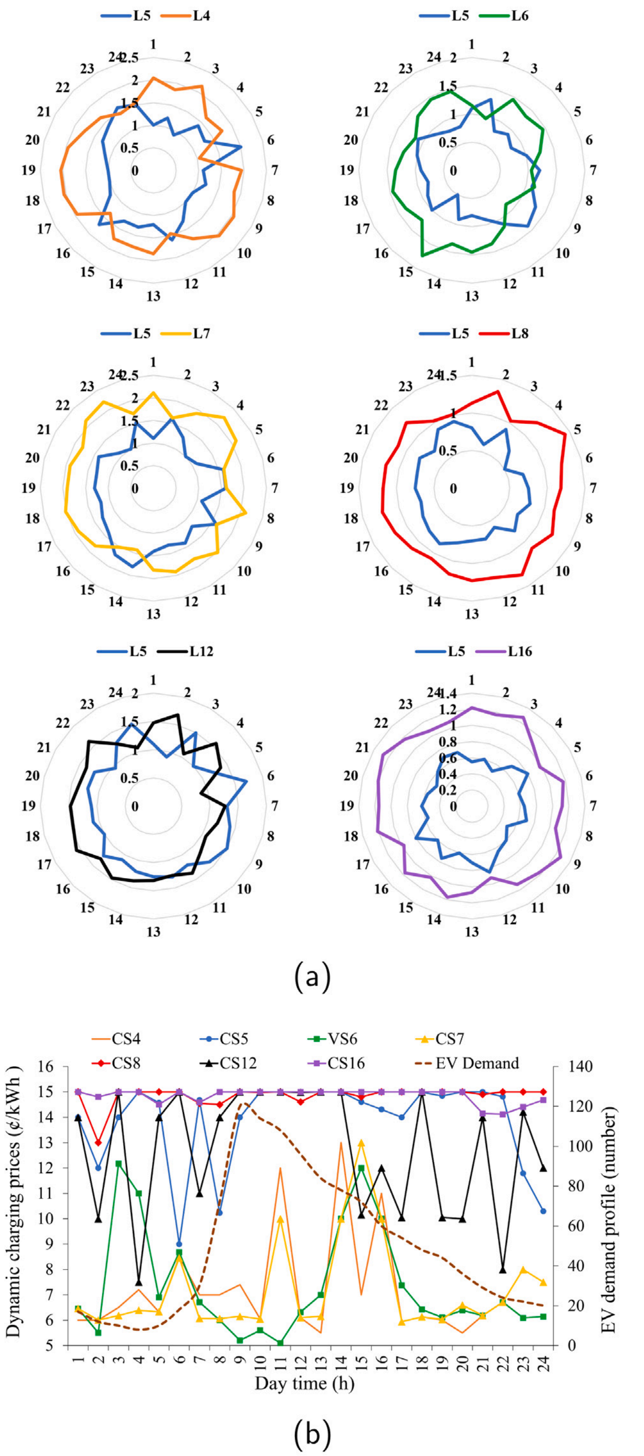

Fig. 9. Impact of dynamic pricing strategy in case IV on CS boundary points; (a) variations in distance from the CS_5 to the boundary points respect to its neighboring CSs; (b) dynamic charging prices of CS_5 and its neighboring CSs along with the EV charging demand.

To analyze the impact of EV charging level, Fig. 10 is presented to compare the plugs occupancy percentage of CSs equipped with the level-2 and DC-fast chargers over all time slots for the dynamic pricing strategy in case III. It is observed that although a limited number of DC-fast chargers are included in this study, CSs with DC-fast chargers are more attractive to the EV users due to their lower charging times as an important factor to the customers. Maximum occupancy rate of CSs

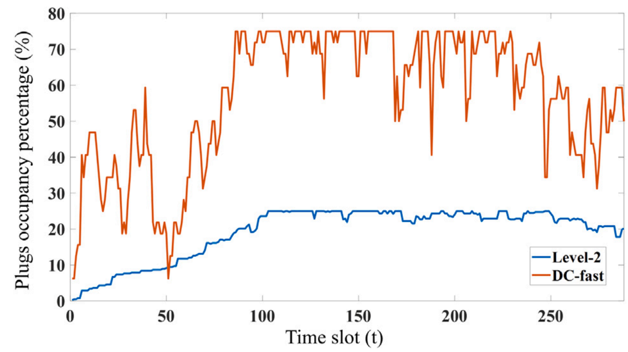

Fig. 10. Comparison of the level-2 and DC-fast charging occupancy percentage during all time slots.

with level-2 charging is about 25% at the peak time, while more than 75% the DC-fast chargers are occupied over the peak demand time. This study shows that DC-fast charging is a promising technology, which leads to both high customer satisfaction and more revenue for the CSO.

5. Conclusions

This work studies the impact of dynamic EV charging pricing strategy on distribution of EVs between CSs. A comprehensive mathematical model is presented in this paper to show how the charging choice of EVs is determined and impacted according to the number of electric plugs, charger types, distances from CS, and charging prices of CS. Then, this model is integrated into a dynamic pricing framework, formulated as a scenario-based stochastic optimization to determine the optimum set of charging prices for each CS over a range of time slots to maximize the overall revenue of CSO. CS locations and EV routes are modeled using QGIS software to consider the realistic routes and distances from EVs to different CSs. Four scenarios of charging pricing strategies including fixed pricing, peak and off-peak pricing, developed dynamic pricing framework in this work, and the proposed dynamic pricing strategy with CSs equipped with online crowd meters are defined and compared in terms of total CSO revenue, customer satisfaction, and congestion of the CSs. The results demonstrate that the proposed dynamic pricing method can increase the total number of charged EVs up to 37.9% and the total revenue of the CSO by 41.5% in comparison with the fixed pricing strategy. Moreover, EV users adjust their selection differently when the CSs are equipped with the online crowd meter, which leads to ~3.2% increase in the amount of energy sold and CSO revenue based on the presented case study. Further, results show that the proposed dynamic pricing strategy improves the user satisfaction level by reducing waiting times at congested CSs. Also, it is observed that CSs equipped with the DC-fast chargers are more attractive to EV users so that they can increase the revenue of CSO by 79%, and reduce charging times of EVs by 7 times on average.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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