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Optimal charging/discharging management strategy for electric vehicles

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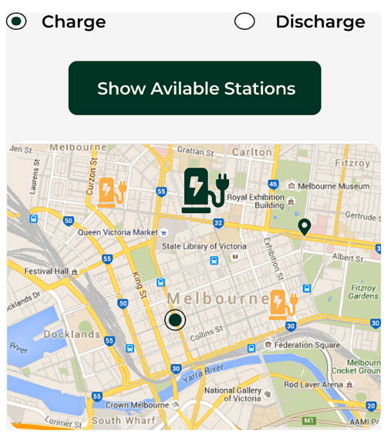
HIGHLIGHTS

- Optimal EV allocation balances energy trading and response time.
- Comprehensive model considers mobility, V2G, G2V, response, and prices.
- GAMS simulations show consistently high EV satisfaction levels.
- Superior outcomes compared to COP and EVaaS models in satisfaction.
- Future work targets an emergency model for EVs with low energy levels.

GRAPHICAL ABSTRACT



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ABSTRACT

Electric vehicles (EVs) are experiencing substantial investment and widespread acceptance. However, successful penetration of the global market is contingent upon the development of a strategic plan for the efficient allocation of EVs to optimal charging stations (CSs). This study combines several optimization models to systematically assign EVs to the optimal charging stations, with the goal of maximizing trading energy while simultaneously minimizing total response time. Factors taken into consideration include traveling distance, charging (V2G), and discharging (G2V) energy trading, total response time, and energy prices. The efficacy of the combined models is validated using GAMS and BARON solvers, with a focus on EV satisfaction factor, updated energy and response time, number of served EVs, and alleviation of range anxiety. The proposed models demonstrate 85% satisfaction factor for the majority of charging requests, reaching almost 99% for discharging

Abbreviations: Full name, Abbreviations; Electric vehicle, EV; Charging station, CS; Vehicle to Grid, V2G; Grid to Vehicle, G2V; Software-Defined Networking, SDN; Smart grid, SG; Plugin electric vehicle, PEV; Quality of service, QoS; Vehicle-to-Infrastructure, V2I; Vehicle-to-Vehicle, V2V; State of charge, SOC; General Algebraic Modeling System, GAMS; Energy Charging Time Model, ECTM; Energy Discharging Time Model, EDTM.

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requests. These results surpass those of contemporary models, underscoring the heightened effectiveness of the proposed approach.

1. Introduction

The transportation sector stands out as a significant contributor to climate pollution. Electrifying transportation emerges as a viable remedy to this issue, given its capacity for zero-carbon emissions. However, the incorporation of electric vehicles (EVs) encounters several challenges. Additionally, the availability of charging facilities for electric vehicles remains limited and uneven, confronting obstacles related to technology, economics, and procedural impediments [1,2]. Nevertheless, the charging patterns of EV users tend to be erratic and unpredictable, thereby presenting challenges for effective grid control [3]. This unpredictability can potentially compromise voltage quality and overall power system stability, particularly as a considerable number of EVs become integrated into the grid [3]. Furthermore, the allocation of charging and discharging schedules for plugin electric vehicle (PEVs) encounters various challenges, including issues related to communication reliability and responsiveness, demand/supply dynamics, battery degradation, range anxiety, computation capacity, and the pursuit of multiple objectives for both PEVs and charging stations (CSs), such as maximizing profits, minimizing costs, and optimizing the quality of service (QoS) [3,4]. Fortunately, the implementation of a coordinated charging and discharging strategy enables EVs to interact with the grid via aggregators and intelligent two-way chargers during periods of surplus availability [1]. This is facilitated by the swift response characteristics of EVs and their extended periods of inactivity throughout their life cycle [1], embodying the concept known as vehicle-to-grid (V2G) [3]. The fundamental idea involves directing EVs to charge during low-demand periods and discharge excess energy to the grid during peak-demand periods [2]. This approach enables users to capitalize on the revenue generated from discharging during peak hours, leveraging the price differential between peak and off-peak periods. Not only does this strategy fulfill the grid's peak-shaving requirements, but it also reduces the overall charging costs for users [2,3].

Addressing the challenges associated with supporting EVs necessitates the development of two key infrastructures: a reliable communication infrastructure capable of facilitating data transfer between EVs and the grid, and a well-established network of charging stations deployed within urban areas, for instance. Both of these challenges require effective management. Considerable progress has been made in addressing the first challenge, with significant effort invested in designing a reliable communication infrastructure, particularly leveraging technologies such as 5G and Software-Defined Networking (SDN) to enhance the reliable exchange of data among EVs, charging stations, and the grid. While numerous papers in the literature explore solutions to this communication infrastructure challenge, it falls outside the scope of the current study. Conversely, this work focuses on a critical aspect related to the second infrastructure, namely the management of EV charging, charging stations, and vice versa. Numerous studies have delved into this aspect.

Much of the current literature on PEVs places specific emphasis on integrating SDN technology into the smart grid (SG). Considering the challenges associated with the secure and effective exchange of information among EVs, meters, CSs, and the power grid, Cai et al. developed a hybrid communication network encompassing both Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication [5].

Chen et al. proposed a two-tier SDN-based framework to integrate PEVs charging/discharging with the SG, enhancing system scalability and flexibility [6]. Focusing specifically on discharging energy, Jindal et al. developed an edge-as-a-service framework employing the OpenFlow pattern, presenting a decentralized configuration with dynamic network policies [7]. The authors of [8] designed a communication unit based on an SDN network with three layers to regulate the connection between the grid, PEVs, and electric vehicle supply equipment (EVSEs), specifically addressing the PEVs charging assignment problem. The research presented in [9] emphasized that decoupling the control plane and data plane offers substantial benefits to SG communication frameworks by improving flexibility and automated monitoring functions. In [10], the authors identified three layers for energy exchange between EVs and CS to maximize CS revenue and optimize EV energy prices. The upper layer was designated for CSs, the middle layer for aggregators, and the lower layer for EVs.

The research presented in [11] proposed a new wireless real-time communication network, where EVs communicate with a local station controller installed for each CS set. This local controller communicates with a central station controller situated on a cloud platform, facilitating EV charging/discharging at public stations. In contrast, the investigation conducted in [12] assumed that, for V2G and G2V interactions, EVs could wirelessly communicate with the SG through a roadside unit. Specific communication technologies establish the connection between the SG and all EVs. In addition, the study detailed in [11] was among the early works to address the challenges of plug-in EVs charging and discharging at public supply stations, employing a new cloud computing architecture for the SG.

Chen et al. acknowledged that incorporating cloud computing technology into SG -SDN based systems can address the overhead problem of data flow processing and optimize data management within the SDN controller [6]. Furthermore, Ghorbanian et al. highlighted that, for minimizing real-time data traffic, cloud-based technology is sufficient to facilitate the data transfer of sensitive SG applications and support local data processing [13]. In [8], both EVs and CSs were linked to a centralized cloud server via communication technologies within the SG. Aujla et al. suggested that in a smart city utilizing a cloud-based application, several aggregators could be installed and controlled based on the characteristics of each area for V2G and G2V interactions [10].

The approach proposed in [9] involved a centralized prediction unit for charging EVs, collecting data from each region and forecasting congestion in those locations. Therefore, the computational burden is concentrated on the centralized unit, making the training process for prediction algorithms computationally intensive. Accordingly, the authors recommended investigating the system computation under the condition of integrating edge and cloud-centric systems to achieve improved and faster prediction and optimization results [9].

Contrastingly, emphasizing the security challenges associated with processing and storing data on the Cloud, particularly due to shared storage among multiple users, Ghorbanian et al. highlighted the adoption of fog computing as a strategy to mitigate these security threats [13]. For example, in [14], the scheduling of charging/discharging PEVs at public stations was enhanced by introducing a new SG framework based on distributed Fog computing, aiming to achieve optimality and efficiency. The study outlined how classifying EVs scheduled for V2G charging based on charging activity proved to be an efficient method for V2G implementation. Considering only V2G behavior in the SG, Shen et al. proposed a hybrid fog and cloud computing architecture that includes 5G-based V2G communication networks, aiming to enhance power service providers' service quality and cost-efficiency [15].

In recent years, there has been a surge in literature addressing optimization models for scheduling the charging/discharging of PEVs. It is essential to explore diverse approaches, encompassing charging during non-peak hours, discharging at peak hours, achieving equilibrium between these scenarios, making informed EV price decisions, and selecting appropriate parameters [16]. Consistent with this, the authors in [11] presented a scheduling algorithm that prioritizes and optimizes the waiting time for charging/discharging EVs at public CSs, considering the mobility of EVs rather than traffic-related issues. Simulations results, utilizing actual supply energy data, demonstrated efficiency improvements during peak load times [11]. Similarly, Brinkel et al. discussed the optimization algorithms employed for generating charging schedules and the growing challenge of managing the charging demand of a large number of EVs within a constrained electric grid [17]. These algorithms aim to strike a balance between user preferences, grid constraints, and energy costs, ensuring efficient and cost-effective charging. Furthermore, [18] presented an advanced smart management system designed for EV recharge. Leveraging intelligent algorithms, the system optimizes charging schedules by considering factors such as grid demand, energy costs, and user preferences. Real-time data and communication networks are utilized to enhance the efficiency and reliability of EV charging infrastructure.

Furthermore, Chekired et al. formulated a mathematical model employing multi-priority queuing theory and cut-off discipline, utilizing Markov chains to minimize the waiting time for plugin charging and discharging EVs [14]. Their findings revealed that the rate of arrival charging/ discharging EVs, the values of cut-off, and the busy number of sockets at each public charging station significantly impact the waiting time, time to plugin, energy demand, and supply curve. Introducing a novel EV charging station access equilibrium model, Liu et al. incorporated a M/D/C queueing framework [19]. The model's objective was to optimize decision-making processes for EV users when selecting charging stations, considering factors such as charging station availability, service times, and user preferences. This study offered a comprehensive framework for understanding and analyzing the equilibrium behavior of EV users in a charging network, ultimately contributing to the efficient utilization of EV charging infrastructure. Additionally, Aljaidi et al. presented a mathematical queueing model considering factors such as EV battery state, charging station capacity, and user preferences [20]. The proposed algorithm aimed to minimize charging time and waiting time for EVs, albeit without considering travel time.

Alternatively, some researchers focused on the demand-supply problem. For instance, Aujla et al. presented a charging/discharging model designed to address the demand-supply issue, allowing EVs to engage in energy selling and buying, thereby enabling profit generation [8]. In another the authors examined the charging assignment problem for PEVs within an integrated architecture consisting of communication, optimization, and prediction units to select the optimal CS [9]. Considering the practical implementation of CSs, the proposed framework underwent testing using a case study, revealing that EVs play a dual role in managing energy demand and maximizing profits for both EVs and CSs [9] [8]. Additionally, [21] focused on improving the efficiency and fairness of EV charging infrastructure by tailoring charging assignments based on individual vehicle preferences and real-time demand. Through the implementation of distributed ledger technology, the study demonstrated how decentralized decision-making can enhance transparency, security, and scalability in EV charging networks, ultimately contributing to the sustainable integration of EVs into the energy grid.

The application of the Stackelberg game proves beneficial in a dynamic framework where CSs cannot unilaterally decide on pricing, and EVs also play a role in these decisions [16]. For instance, [10] introduced two scenarios for energy exchange between EVs and CSs using the Stackelberg game as a multi-leader multi-follower approach, aiming to maximize CS revenue and optimize EV energy prices. The same study proposed dynamic energy pricing through multi-parameter adjustments based on factors such as time of use, amount of use, class of EVs, and the position of CSs, influencing the pricing structure. The simulation results analyzed in the study demonstrated that the scenario where EVs act as leaders and CSs as followers is more profitable for both CSs and EVs, consistently maintaining a satisfaction factor close to the highest value for EVs [10].

Some studies have focused on addressing the assignment problem in the context of EVs charging. In [22], a decentralized stochastic technique was introduced to suggest the most suitable CS for EVs charging, taking into account various utility functions. The authors in [20] proposed a new approach that addresses the allocation problem by considering multiple factors, such as the displacement between the current position of the EV and the CS, the difference in elevation between their positions, and the capacity of the CS.

In recent years, there has been a notable surge in the application of reinforcement learning (RL) techniques to address the allocation of EVs to CSs, garnering substantial attention within the research community. Introducing RL charging as a novel approach for recommending optimal charging stations for electric vehicles (EVs), Zhang et al. employed imitative multi-agent spatiotemporal RL [23]. RL charging utilizes RL techniques to model the dynamic and spatial aspects of EV charging demand. The system adopts a multi-agent framework to capture complex interactions between charging stations and users, thereby enhancing the recommendation process. Furthermore, [24] presented a novel RL-based Assignment Scheme for EVs to CS. The proposed scheme aims to optimize the allocation of EVs to charging stations dynamically and efficiently. Utilizing RL techniques, the system learns to make intelligent decisions in real-time, considering factors such as EV battery state, station availability, and user preferences. Experimental results demonstrate the effectiveness of the proposed scheme in reducing charging wait times and maximizing overall system efficiency, positioning it as a promising approach for managing EV charging infrastructure. Similarly, the authors of [25] proposed a data-driven approach that utilizes real-time data and advanced algorithms to optimize charging schedules for each EV in the fleet. This approach considers factors such as battery state of charge, energy demand, and charging infrastructure availability. By analyzing historical charging data and adapting to real-time conditions, the system aims to minimize charging costs and reduce the environmental impact of EV fleets. The study delves into the key components of the data-driven smart charging system, including data collection from EVs, cloud-based data processing, and optimization algorithms. Moreover, some studies have presented a hybrid control framework that combines policy gradient methods with rule-based algorithms to enhance the efficiency of EV charging systems. For example, the research in [26] addresses challenges associated with EV charging, including managing charging schedules, minimizing costs, and ensuring user satisfaction. To achieve these objectives, the authors proposed a hybrid control strategy that integrates RL techniques from the policy gradient family with predefined rules for decision-making. The policy gradient component of the framework is responsible for learning optimal charging policies through interactions with the EV charging system. By leveraging RL, the model adapts and improves its charging strategies over time, considering dynamic factors such as electricity pricing, grid load, and user preferences.

However, prior research has neglected the exploration of a unified G2V and V2G architecture as a multi-objective optimization problem aimed at identifying the optimal CS. The optimization involves maximizing energy and minimizing the total response time, which comprises traveling time, waiting time, and charging time. This paper seeks to evaluate various models for allocating EVs to the optimal CS, considering multi-objective functions such as maximizing requested energy and minimizing total response time for both V2G and G2V interactions. We integrated an energy charging model based on state of charge (SOC) with the total response time model, accounting for travel time, charging service time, and waiting time at the CS. Likewise, we merged the energy discharging model, utilizing SOC, with the total response time. Therefore, the outputs of these proposed models serve as input parameters for the assignment problem. To consolidate multiple objectives into a unified model, we focused solely on the energy objective, while constraining the time objective based on driver-specific expectations using the ε-Constraint Method. Finally, to validate the proposed models, we used General Algebraic Modeling System (GAMS) and the BARON solver. GAMS, a widely used modeling language, and BARON, a state-of-the-art optimization solver, were selected for their capability to handle complex mathematical models and nonlinear programming.

The contributions of this study can be summarized as follows:

1. We combined the energy charging model, based on the SOC, with the total response time model, incorporating traveling time, charging service time, and waiting time at the CS for plugin. These integrated models are called the Energy Charging Time Model (ECTM).
2. Similarly, we integrated the energy discharging model based on the SOC with the total response time model, incorporating traveling time, discharging service time, and waiting time at the CS for plugin. These integrated models are called the Energy Discharging Time Model (EDTM).
3. The objective of the assignment problem is to determine the optimal CS by maximizing the required energy and minimizing the total response time. The outputs of ECTM and EDTM serve as parameters input for the assignment problem. To consolidate the multiple objectives into a unified model, we focused solely on the energy objective and restricted the time objective within driver-specific expectations using the ε-Constraint Method.

The remaining sections of the paper are structured as follows. Section III provides an overview of the system in this research. Section IV introduces the ECTM and the EDTM, along with their mathematical models for the assignment problem. Results and discussions are presented in Section V, followed by conclusions in Section VI.

2. System overview

2.1. Problem statement

Let I represent the number of electric vehicles distributed across an area A. to the objective is to assign each i^{th} EV to a charging station, aiming to maximize the total energy attained by all EVs, while minimizing the summation of traveling times, waiting plugin times, and charging/discharging times. In addition, the goal is to increase the number of served EVs in the system, thereby minimizing range anxiety. It is assumed that the available communication infrastructure possesses sufficient capacity to handle all required information exchanges.

The power supply is considered to be obtainable from both the grid (G2V) and the electric vehicle to the grid (V2G). Different models of electric vehicles, such as Toyota Prius, Chevy Spark, and Mitsubishi iMiEV, are taken Into account, each with its specific battery characteristics. The developed optimization model incorporates various factors including EVs mobility, SOC for each vehicle, electricity selling/buying prices, and satisfaction factors for both EVs and CSs.

2.2. Mobility model

Every city is divided into d blocks, following a Manhattan block city architecture. Each block contains a number of CSs $s = \{1, \dots, S\}$ and EVs i = {1…,I}, as shown in Fig. 1. The primary factor influencing CS selection for EVs is the distance from the EV location to the CS location within the same block. Consequently, each CV will prioritize exchanging energy with the nearest CS in its block. However, if a CS in a different block offers a lower energy price or total response time and is willing to travel and charge/discharge, the EV may be assigned to go to that block, particularly if the results of the mobility model are used in the energy trading models.

The distance from the location of EV i to CS s is calculated using Rectilinear Distance, representing the distance along paths that are perpendicular to each other exclusively. If (x_i, y_i) denotes the location coordinates of EV i and (x_s, y_s) denotes the location coordinates of CSs, then the distance is given by:

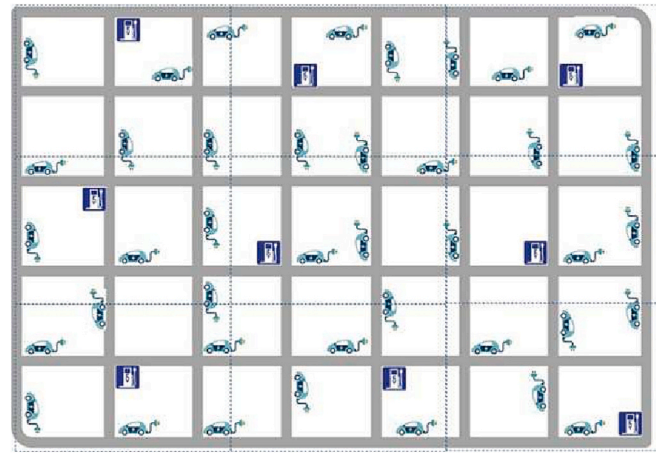

Fig. 1. Model of EV mobility in an urban city [8].

$$d_{i\rightarrow s} = |x_s - x_i| + |y_s - y_i|. \tag{1}$$

3. Optimization models

In this section, we discuss the two proposed models: (1) ECTM and (2) EDTM. It is noteworthy that the basic definitions are adopted from [8], unless explicitly stated otherwise.

3.1. Energy charging time model (ECTM)

In this model, EVs request to charge energy from CSs with the aim of reaching the maximum energy level. Each EV model is equipped with a charging battery having a different rated capacity. The required SOC for i^{th} EV to achieve the maximum level is defined as follows.

$$SOC_i^{req} = SOC_i^{max} - SOC_i^{prs}, \tag{2}$$

where the present SOC for the i^{th} EV is SOC_i^{prs} and SOC_i^{max} is the maximum SOC level of the i^{th} EV. Consequently, the required energy for the i^{th} EV to reach the maximum level is given by:

$$E_i^{req} = SOC_i^{req} \times E_i^{rt}, \tag{3}$$

where E_i^{rt} is the rated energy capacity of the EV i battery, representing the maximum capacity of i^{th} EV's battery.

The energy available at CSs, denoted as SOC_s^{avl}, is calculated as the present SOC at CSs SOC_s^{prs} minus the SOC threshold SOC_s^{thr}:

$$SOC_s^{avl} = SOC_s^{prs} - SOC_s^{thr}. \tag{4}$$

The energy available at CSs E_s^{avl} is calculated as:

$$E_s^{avl} = SOC_s^{avl} \times E_s^{rt}, \tag{5}$$

where E_s^{rt} is the rated battery pool capacity of the CSs.

To ensure that CSs meet the requested EV energy, the present SOC at CSs SOC_s^{prs} should be greater than the threshold SOC SOC_s^{thr}:

$$SOC_s^{prs} > SOC_s^{thr}. \tag{6}$$

The model then selects the optimal CS, and the EV pays a fixed price, assuming a fixed pricing structure as on the Hawaiian Electric Company website. The SOC of the EV is updated as follows:

$$SOC_i^{upd} = SOC_i^{prs} + SOC_{s\rightarrow i}^{giv} - SOC_{i\rightarrow s}^{trv}. \tag{7}$$

The updated SOC $\left(SOC_i^{upd}\right)$ for i^{th} EV is equal to the present SOC $\left(SOC_i^{prs}\right)$ plus the SOC given from CSs $\left(SOC_{s\rightarrow i}^{giv}\right)$ minus the consumed

SOC during traveling from the location X to CSs $\left(SOC_{i\to s}^{trv}\right)$.

The updated energy for the i^{th} EV is given by:

$$E_i^{upd} = SOC_i^{upd} \times E_i^{rt}. \tag{8}$$

The SOC wasted by the i^{th} EV while traveling to CSs $SOC_{i\to s}^{trv}$ is calculated as:

$$SOC_{i\to s}^{trv} = \frac{d_{i\to s}}{D_i^{max}} * SOC_i^{max}, \tag{9}$$

where D_i^{max} is themaximum distance of the i^{th} EV with respect to all available CSs.

The required energy by the i^{th} EV to travel to CSs $E_{i\to s}^{trv}$ is computed as follows:

$$E_{i\to s}^{trv} = SOC_{i\to s}^{trv} \times E_i^{rt}. \tag{10}$$

Now, considering the case of the charging station, the updated SOC $\left(SOC_s^{upd}\right)$ for CSs is equal to the present SOC $\left(SOC_s^{cur}\right)$ minus the SOC charged from CSs $\left(SOC_{s\to i}^{giv}\right)$:

$$SOC_s^{upd} = SOC_s^{prs} - SOC_{s\to i}^{giv}. \tag{11}$$

The updated energy for CSs is given by:

$$E_s^{upd} = SOC_s^{upd} \times E_s^{rt}. \tag{12}$$

The required energy by the i^{th} EV should be less than or equal to the rated battery capacity:

$$0 < E_i^{req} \le E_i^{rt} \forall i. \tag{13}$$

The energy available at the CSs should be less than or equal to the rated battery capacity:

$$0 < E_s^{avl} \le E_s^{rt} \forall s. \tag{14}$$

To evaluate the total response time, it is necessary to compute the following time components.

- The time slot in which the i^{th} EV arrives at the CSs is given by [9]:

$$\tau_n = \frac{T_i + T_{i\to s}^{trv}}{\tau}, \tag{15}$$

where T_i is the time when the i^{th} EV makes the request, $T_{i\to s}^{trv}$ is the traveling time, and τ is the length of the time slot period.

- The traveling time for the i^{th} EV to travel from its present location to the CS location is calculated as [9]:

$$T_{i\to s}^{trv} = \frac{d_{i\to s}}{S_i}, \tag{16}$$

where S_i is the average speed for the i^{th} EV.

- The service charging time for the i^{th} EV at CSs is given by [9]:

$$T_{i,s}^{ch} = \left\{SOC_i^{req} - \left(SOC_i^{prs} - R_i^{dis} \times d_{i\to s}\right)\right\} \times R_s^{ch}, \tag{17}$$

- where R_i^{dis} is the discharging rate for the i^{th} EV, and R_s^{ch} is the charging rate at CSs.
- The waiting time for the i^{th} EV at CSs is calculated as [9]:

$$T_{i,s}^{w} = \Gamma \times \hat{y}_{s,n}, \tag{18}$$

where Γ is a constant chosen arbitrarily, and $\hat{y}_{s,n}$ is the predicted traffic arriving at the CSs at time slot n.

Thus, the total response time for the i^{th} EV to charge at the CSs can be computed as follows:

$$T_{i,s}^{crs} = T_{i\to s}^{trv} + T_{i,s}^{w} + T_{i,s}^{ch}. \tag{19}$$

The satisfaction level of the EV after charging, considering updated energy and response time, is defined as follows:

$$S_i^{ch} = \frac{E_i^{upd}}{E_i^{rt}} \times \alpha + \aleph \times \beta. \tag{20}$$

The first term measures how much energy has been acquired comapred to its maximum capacity. Of course, as an EV user, he likes to maximimze this ratio. $\aleph$ is defined as

$$\aleph = \begin{cases} 1, \text{if } \dfrac{T_{i,s}^{avl}}{T_{i,s}^{crs}} > 1 \\ \dfrac{T_{i,s}^{avl}}{T_{i,s}^{crs}}, \text{otherwise} \end{cases}$$

Where $T_{i,s}^{avl}$ is the desired response time. Each term may have different importance, as defined by α, β which are percentages representing the importance of the factor level. The satisfaction level is then obtained by adding these terms.

The outputs of the previous quantities are used in the assignment problem. To formulate the assignment problem, we have the following:

Decision variables:

$$X_{i,s} = \begin{cases} 1, \text{if } ith \text{ EV is assigned to the CSs} \\ 0, \text{otherwise} \end{cases}$$

Objective functions:

Maximizing the energy required for each EV:

$$Max\ CH = a_i \sum_{i}^{I} ln\left(b_i + E_i^{req} \times p_s \times X_{i,s} - E_{i\to s}^{trv} \times p_s \times X_{i,s}\right). \tag{21}$$

Minimizing the total response time:

$$Min\ CRT = \sum_{i}^{I} \sum_{s}^{S} T_{i,s}^{crs} \times X_{i,s}, \tag{22}$$

where a_i and b_i are constants, and p_s is the price announced by the CS.

Constraints:

1. Every EV is assigned to only one CS

$$\sum_{s} X_{i,s} \le 1, \forall i \tag{23}$$

2. The overall energy supplied by CSs to all EVs assigned should be less than or equal to the available energy at that CS

$$\sum_{i=1}^{I} E_{s\to i}^{giv} \times X_{i,s} \le E_s^{avl}, \forall s \tag{24}$$

3. The energy supplied to i^{th} EV is less than or equal to the energy required by the same EV

$$\sum_{s=1}^{S} E_{s\to i}^{giv} \times X_{i,s} \le E_i^{req} \forall i \tag{25}$$

4. Every EV should have enough revenue (V_i) to pay for the energy price

$$\sum_{s=1}^{S} p_s \times E_i^{req} \times X_{i,s} \le V_i, \forall i \tag{26}$$

5. The energy updated for i^{th} EV is given by

$$E_i^{upd} = E_i^{prs} + E_{s\to i}^{giv} - \sum_{s=1}^{S} E_{i\to s}^{trv} \times X_{i,s}, \forall i \tag{27}$$

6. The energy updated for CS s is calculated as

$$E_s^{upd} = E_s^{avl} - \sum_{i=1}^{I} E_{s\rightarrow i}^{giv} \times X_{i,s}, \forall s \tag{28}$$

7. The energy updated for i^{th} EV should be less than the battery capacity for the same EV

$$E_i^{upd} < E_i^{rat} \tag{29}$$

8. The energy supplied for i^{th} EV should be greater than the traveling energy

$$\sum_{s=1}^{S} E_{i\rightarrow s}^{trv} \times X_{i,s} < E_{s\rightarrow i}^{giv} \tag{30}$$

9. The total response time should be less than or equal to the maximum estimated response time

$$\sum_{i}^{I} \sum_{s}^{S} T_{i,s}^{crs} \times X_{i,s} \leq \varepsilon, \tag{31}$$

where ε is a constant value.

10. The total number of EVs charging at CSs should be less than or equal to the CS capacity C_s

$$\sum_{i} X_{i,s} \leq C_s \forall s \tag{32}$$

11. Binary variable

$$X_{i,s} = \{0, 1\} \forall i, s \tag{33}$$

12. None negativity

$$T_{i,s}^{crs}, E_{s\rightarrow i}^{giv}, E_i^{upd} \geq 0 \tag{34}$$

3.2. Energy discharging time model (EDTM)

In this model, EVs request to supply (i.e., discharge) energy to CSs to reach the maximum energy level for selling at a reasonable price. The SOC available with the i^{th} EV $\left(SOC_i^{avl}\right)$ is equal to the present SOC at i^{th} EV $\left(SOC_i^{prs}\right)$ minus the SOC threshold $\left(SOC_i^{thr}\right)$:

$$SOC_i^{avl} = SOC_i^{prs} - SOC_i^{thr}. \tag{35}$$

The energy available at the i^{th} EV, E_i^{avl}, is given by:

$$E_i^{avl} = SOC_i^{avl} \times E_i^{rt}. \tag{36}$$

To ensure that the i^{th} EV can participate in the discharging process, the present SOC at the i^{th} EV $\left(SOC_i^{cur}\right)$ should be greater than the threshold SOC SOC_i^{thr} [8].

$$SOC_i^{prs} > SOC_i^{thr} \tag{37}$$

Every CS is supplied by two primary sources: renewable energy sources (PV panels) and discharging EVs. The calculation for the maximum energy at every CS is as follows.

$$E_s^{prs} = E_s^{ren} + \sum_{i=1}^{I} E_i^{dis} \tag{38}$$

The required SOC for CSs to reach the maximum level is:

$$SOC_s^{req} = SOC_s^{max} - SOC_s^{prs}. \tag{39}$$

The energy required by CSs, E_s^{req}, is:

$$E_s^{req} = SOC_s^{req} \times E_s^{rt}, \tag{40}$$

where E_s^{rt} is the rated battery pool capacity of the CSs.

The EVs participating in the discharging process will select the optimal CS and discharge their energy. The CS will pay for the energy discharged by the EV.

$$SOC_s^{upd} = SOC_s^{prs} - SOC_{i\rightarrow s}^{dis} \tag{41}$$

The updated SOC $\left(SOC_s^{upd}\right)$ for CSs is equal to the present SOC $\left(SOC_s^{prs}\right)$ minus the SOC discharged from the i^{th} EV $\left(SOC_{i\rightarrow s}^{dis}\right)$.

The updated energy for CSs is calculated as:

$$E_s^{upd} = SOC_s^{upd} \times E_s^{rt}. \tag{42}$$

After discharging, the updated SOC $\left(SOC_i^{upd}\right)$ for the i^{th} EV is equal to the present SOC $\left(SOC_i^{prs}\right)$ minus the SOC given to the CS $\left(SOC_{i\rightarrow s}^{giv}\right)$ minus the SOC consumed during traveling from the EV location to the CS $\left(SOC_{i\rightarrow s}^{trv}\right)$.

$$SOC_i^{upd} = SOC_i^{prs} - SOC_{i\rightarrow s}^{giv} - SOC_{i\rightarrow s}^{trv} \tag{43}$$

The updated energy for the i^{th} EV is given by:

$$E_i^{upd} = SOC_i^{upd} \times E_i^{rt}. \tag{44}$$

The energy required by CSs should be less than or equal to the rated battery capacity:

$$0 < E_s^{req} \leq E_s^{rt}, \forall s. \tag{45}$$

The present energy available at CSs should be less than or equal to the rated battery capacity:

$$0 < E_s^{prs} \leq E_s^{rt}, \forall s. \tag{46}$$

Every CS should have enough revenue (V_s) to pay for the energy price:

$$\sum_{s=1}^{S} \sum_{i=1}^{I} p_i \times E_s^{req} \leq V_s. \tag{47}$$

The energy price announced by the i^{th} EV is given by [8]:

$$P_i = \delta \times \left(\frac{SOC_i^{max}}{SOC_i^{avl} - SOC_i^{thr}} \right), \tag{48}$$

where δ is a constant to ensure that the overall price is always greater than the purchasing price.

The total response time is calculated using the same procedure as in ECTM. The time slot in which the i^{th} EV arrives at CSs is calculated using (15). The traveling time for the i^{th} EV to travel from its present location to the CS location is given by (16). In contrast, the service discharging time for the i^{th} EV at CSs can be computed as in (49).

$$T_{i,s}^{dis} = \left\{ \left(SOC_i^{prs} - R_i^{dis} \times d_{i\rightarrow s} \right) - SOC_i^{thr} \right\} \times R_s^{dis} \tag{49}$$

Eq. (18) presents the waiting time for the i^{th} EV at CSs. The total response time for the i^{th} EV to discharge at CSs is given by:

$$T_{i,s}^{drs} = T_{i\rightarrow s}^{trv} + T_{i,s}^{w} + T_{i,s}^{dis}. \tag{50}$$

The EVs satisfaction level after discharging, considering the sold energy and response time, can be expressed as follows [8]:

$$S_i^{dis} = \frac{E_{i\rightarrow s}^{giv}}{E_i^{avl}} \times \alpha + \aleph \times \beta, \tag{51}$$

where α *and* β are percentages representing the importance of the factor level, and $\aleph = 1$ if $\frac{T_{i,s}^{avl}}{T_{i,s}^{drs}} > 1$ and 0 otherwise.

The output of the previous equations is used in the assignment problem. To formulate the assignment problem, we have the following:

Decision variables:

$$X_{i,s} = \begin{cases} 1, \text{if the } ith \text{ EV is assigned to the CSs} \\ 0, \text{otherwise} \end{cases}$$

Objective function:

Maximizing the energy required for every CS [8]:

$$Max\ DSH = a_s \sum_{s}^{S} ln\left(b_s + E_s^{req} \times p_i \times X_{i,s}\right) \tag{52}$$

Minimizing the total response time:

$$Min\ DRT = \sum_{i}^{I} \sum_{s}^{S} T_{i,s}^{drs} \times X_{i,s}, \tag{53}$$

where a_i and b_i are constants, and p_s is the price announced by the CS.

Constraints:

1. Every EV is assigned to only one CS

$$\sum_{s} X_{i,s} \leq 1, \forall i \tag{54}$$

2. Every CS should have enough revenue (V_s) to pay for the energy price

$$\sum_{i=1}^{I} p_i \times E_i^{req} \times X_{i,s} \leq V_s, \forall s \tag{55}$$

3. Energy updated for EV i is given by

$$E_i^{upd} = E_i^{prs} - E_{i\rightarrow s}^{dis} \times X_{i,s} - \sum_{s}^{S} E_{i\rightarrow s}^{trv} \times X_{i,s}, \forall i \tag{56}$$

4. Energy updated for CSs is calculated as

$$E_s^{upd} = E_s^{prs} + E_s^{ren} + \sum_{i}^{I} E_{i\rightarrow s}^{dis} \times X_{i,s}, \forall s \tag{57}$$

5. Updated energy at CSs should be less than or equal to the rated pool capacity

$$E_s^{prs} + E_s^{ren} + \sum_{i}^{I} E_{i\rightarrow s}^{dis} \times X_{i,s} \leq E_s^{rat}, \forall s \tag{58}$$

6. The total response time should be less than or equal to the maximum estimated response time

$$\sum_{i}^{I} \sum_{s}^{S} T_{i,s}^{drs} \times X_{i,s} \leq \varepsilon, \tag{59}$$

where ε is a constant value.

7. The total number of EVs discharging at CSs should be less than or equal to the CS capacity C_s

$$\sum_{i} X_{i,s} \leq C_s \forall s \tag{60}$$

8. Binary variable

$$X_{i,s} = 0, 1 \forall i, s \tag{61}$$

9. None negativity

Table 1
Specifications of charging stations.

Charging station	Charger type	Public access	Time of use period	Price ($/kWh)
Oahu (1)	DC Fast Charger	24 h	Mid-Day (9 a.m.–5 p.m.)	0.49
Maui (2)	DC Fast Charger	24 h	Mid-Day (9 a.m.–5 p.m.)	0.49
Molokai (3)	DC Fast Charger	24 h	Mid-Day (9 a.m.–5 p.m.)	0.54
Hawaii Island (4)	DC Fast Charger	24 h	Mid-Day (9 a.m.–5 p.m.)	0.51

$$T_{i,s}^{drs}, E_s^{upd}, E_i^{upd}, E_{i\rightarrow s}^{dis} \tag{62}$$

4. Results and discussion

The developed models underwent testing in a case study involving 40 EVs distributed across six different EVs (Toyota Prius, Chevy spark, Mitsubishi iMiEV, BMW i3, Nissan Leaf, and Tesla S) and four charging stations. The case study was conducted in an urban area (5 × 5 km^2), organized in a Manhattan layout. We used actual CSs data from the Hawaiian Electric Company website [27], and the details are summarized in Table 1. Additional parameters for the CSs are presented in Table 2.

The coordinates of the CSs locations (x,y) are randomly generated using a uniform distribution. Specifically, the x-coordinate is generated within the range [0,25] and the y-coordinate is chosen from a discrete set of values [0,5,10,15,20,25]. Similarly, the coordinates of the EVs locations (x, y) are also generated using the same random process.

During the mid-day time period, requests are collected within 15 s, and charging stations are allocated accordingly. The request time is determined by generating a random number between 0 and 15. Subsequently, traveling time as well as charging and discharging times are calculated based on the time response model. The average speed is fixed for all EVs to be 50 km/h, ensuring that traveling speed does not significantly influence the allocation process, with the distance being the critical factor.

In contrast, waiting and discharging/charging times vary among CSs due to different discharging/charging rates. These rates are randomly generated using Table 3. For waiting times to plugin, probabilities obtained from a prior study [9] are utilized, with waiting times being 0.28, 0.4, 0.32, and 0.34 for CSs 1, 2, 3, and 4, respectively. These waiting times are applied uniformly across all EVs.

The present SOC for each EV and CS is randomly generated using a uniform distribution within the range [0,100]. A value of 100 implies that the EV is fully charged, while a value of 0 signifies an empty battery. Additionally, the rated energy capacity is randomly assigned using

Table 2
Charging station parameters.

Parameter	Value
a	1.5
b	1
SOC_s^{thr} (*charging*)	50%
SOC_s^{thr} (*discharging*)	50%
E_s^{rt}	100 *kWh* [8]

Table 3
Time response model parameters.

Discharge rate	0.1–2.5 kWh/mile
Charging rate	1–5 kWh
EV avg. speed	50 km/h
ε	30 (min)

Table 4
EVs battery specifications.

Model	Battery capacity E_i^{rt} (kWh)	Electric range (km)	Charging voltage (VAC)	Charging current (A)
Toyota Prius	4.4	18	230	15
Chevy spark	21.3	132	230	15
Mitsubishi iMiEV	16	128	230	15
BMW i3	22	160	230	30
Nissan leaf	24	160	230	30
Tesla S	70	390	265	40

Table 5
Machine specifications.

Processor	Intel(R) Xeon(R) W—1290P CPU @ 3.70GHz 3.70 GHz
Installed RAM	32.0 GB
System type	64-bit operating system, x64-based processor

Table 4. Subsequently, based on SOC_i^{thr}, we further classify the EVs' requests into charging and discharging groups. If SOC_i^{prs} is less than or equal to SOC_i^{thr}, the request is considered as a charging request; otherwise, it is treated as a discharging request. For charging requests, EVs are assigned to the optimal CS if SOC_i^{prs} is greater than or equal to the minimum $SOC_{i\rightarrow s}^{trv}$; otherwise, the EV will not be served.

The specifications of the machine used for running the program are summarized in Table 5. The obtained figures are resulted from averaging 10 rounds of optimization, where we achieved 95% confidence level.

Table 6 summarizes the optimal assignments based on the proposed models. In this scenario, there are 20 charging requests. Ten of these {1,9,12,21,23,29,31,33,34,38} can reach the nearest CSs with their present SOC; while the other ten {5,10,13,14,15,18,20,28,32,39} are unable to travel to any CS. The first group of EVs utilizes the charging model to select the optimal CS, considering the distance as a primary factor and price along with the total response time as a secondary factor.

Fig. 2 shows the updated energy E_i^{upd} for each charged EV, illustrating that. All assigned EVs are able to acquire a reasonable amount of energy relative to their maximum capacities, as indicated in Table 4. The satisfaction factor for each electric vehicle is presented later. Fig. 3 shows the updated energy E_s^{upd} in each charging station by the end of this scenario.

For the discharging requests, there are a total of 20 such requests. The discharging model will assign these EVs to the optimal CS for discharging. First, the model checks if the EV has sufficient energy to trade with the CS by comparing E_i^{avl} with the minimum $E_{i\rightarrow s}^{trv}$. If E_i^{avl} is greater than the minimum $E_{i\rightarrow s}^{trv}$, then the EV is assigned to the primal CS based on the distance as the primary factor and price along with total response time as secondary factors. Otherwise, the system suggests that this EV should initiate a charging request, and that request is rejected. At the end of this process, 15 requests are rejected, and only five are accepted,

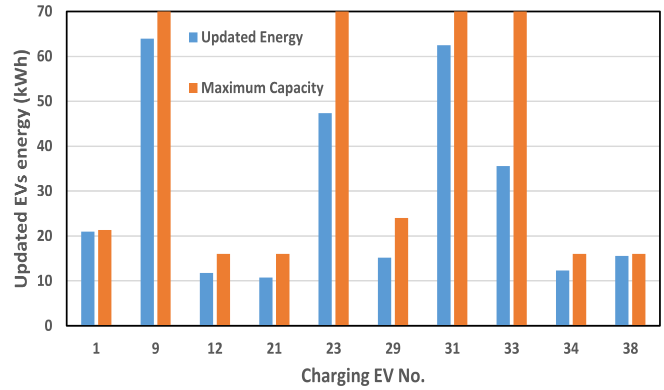

Fig. 2. Updated EVs energy using the charging model.

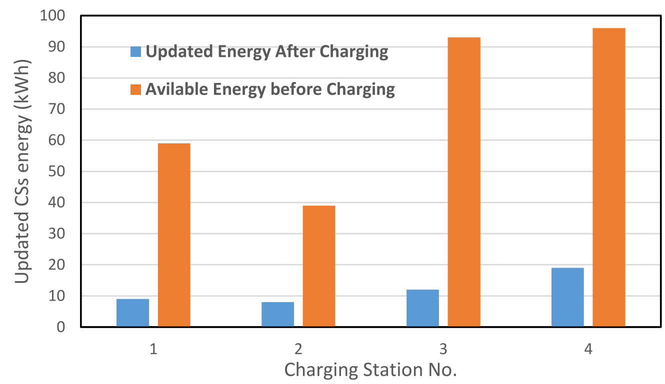

Fig. 3. Updated CSs energy using the charging model.

as detailed in Table 6. The updated energy for both EVs and CSs is shown in Fig. 4 and Fig. 5, respectively.

To validate our models, we conducted a comparative analysis with two recent related works, COP [9] and EVaaS [8], utilizing satisfaction factors (as in Eqs. (20) and (51)). Both approaches involve different optimization models for assigning EVs to CSs, while considering the same mobility model, energy trading, and SOC. The basis for comparison lies in assessing the updated energy and total response time after assigning EVs to CSs. We assumed the same parameters and case study for this comparative analysis. Fig. 6 illustrates the results, demonstrating that our proposed model consistently provides satisfaction levels of 80% and above for all electric charging vehicles. In contrast, COP drops as low as 60%, and EVaaS reaches levels as low as 30%. Additionally, the satisfaction of selected EVs for discharging at charging stations is as high as 100% in our proposed model, surpassing the satisfaction levels achieved by both COP or EVaaS. (See Fig. 7.)

Table 6
Summary of the optimal assignments; the pair {1←4} means CS# 4 is charging EV#1, the pair {7→1} means EV#7 is discharging in CS#1}, and so on.

Type of Service	EVs in in Dis/charge	CS in Dis/charge
G2V (Charging)	{1,9,12,21,23,29,31,33,34,38}	{1←4}{9←4}{12←3} {21←2}{23←1} {29←2}{31←3} {33←3}{34←1} {38←2}
V2G (Discharging)	{7→1}{25→2} {27→2}{35→2} {40→2}	Nominated:{2,3,4,6,7,8,11,16,17,19,22,24,25,26,27,30,35,36,37,40} Accepted:**{7,25,27,35,40}**
Not Served	{5,10,13,14,15,18,20,28,32,39}	

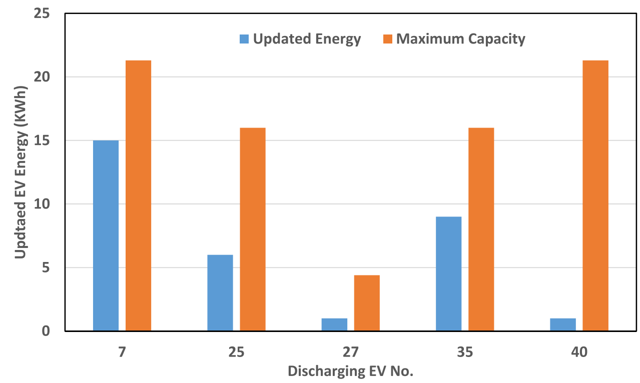

Fig. 4. Updated EVs energy after using the discharging model.

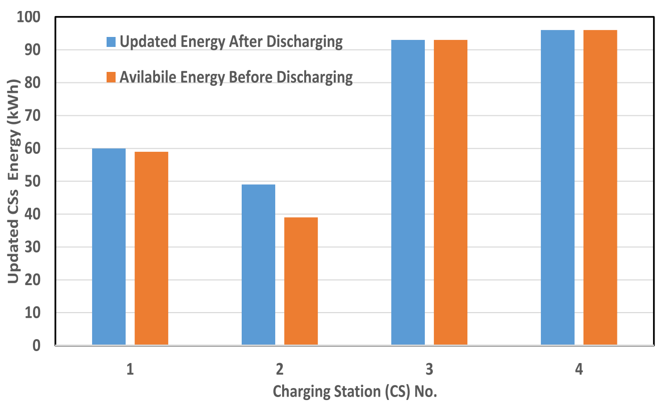

Fig. 5. Updated CSs energy using the discharging model.

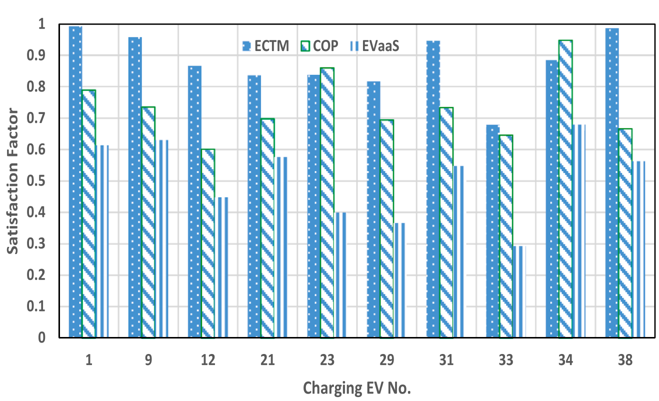

Fig. 6. Satisfaction factor for charging EVs.

5. Conclusion

We proposed two optimization models aimed at efficiently allocating electric vehicles to charging stations, with the goal of maximizing trading energy and minimizing response time. Our proposed models consider various factors, including EV traveling distance, charging (V2G), and discharging (G2V) energy trading, total response time, and energy prices. To assess the effectiveness of our proposed models, we conducted extensive simulations using GAMS. Comparative analysis against two recent related works, COP and EVaaS, revealed that our models consistently achieved high satisfaction levels for both charging and discharging EVs. However, some EVs were left unsupported as they lacked sufficient energy to reach any stations when they sent their requests for charging. As a potential avenue for future work, we plan to

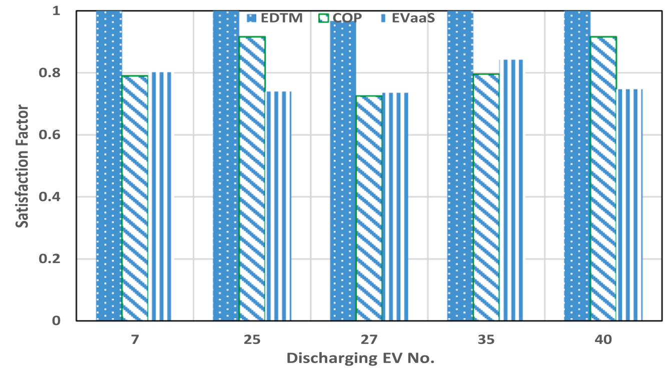

Fig. 7. Satisfaction factor for discharging EVs.

develop an emergency model that can effectively serve these EVs, maximizing both trading energy and the number of served EVs in the system.

It is worth to note that the proposed models are mixed integer nonlinear programming (MINLP) models and the complexity of solving the problem is considered to be NP-hard. As a result, the time required to solve this problem can increase exponentially with the size of the input data. The complexity arises from the combination of both discrete and continuous variables coupled with nonlinear relationships within some constraints. This issue will be tackled in our future work to expedite the computation time.

CRediT authorship contribution statement

Mohammed Algafri: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Uthman Baroudi:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Uthman Baroudi reports a relationship with King Fahd University of Petroleum & Minerals that includes: employment. The authors would like to thank the (DROC) at King Fahd University of Petroleum & Minerals (KFUPM) for the support of this work under project No. DF191006. Uthman Baroudi has patent pending to KFUPM. If there are other authors, they 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

No data was used for the research described in the article.

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