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Dynamic capacitated facility location problem in mobile renewable energy charging stations under sustainability consideration

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ABSTRACT

The deployment of mobile renewable energy charging stations plays a crucial role in facilitating the overall adoption of electric vehicles and reducing reliance on fossil fuels. This study addresses the dynamic capacitated facility location problem in mobile charging stations from a sustainability perspective. This paper proposes Two-stage stochastic programming with recourse that performs well for this application, and the location of the mobile renewable energy charging station (MRECS) management addresses the complex dynamics of reusable items. To solve this problem, we suggested dealing with differential evolutionary (DE) and DE Q-learning (DEQL) algorithms, as two novel optimization and reinforcement learning approaches, are presented as solution approaches to validate their performance. Evaluation of the outcomes reveals a considerable disparity between the algorithms, and DEQL performs better in solving the presented problem. In addition, DEQL could minimize the total operation cost and carbon emission by 7% and 20%, respectively. In contrast, the DE could decrease carbon emissions and total operation costs by 5% and 2.5%, respectively.

1. Introduction

The sustainability of the mobile energy framework rests significantly on the transportation sector. Recent progressions have underscored the imperative of electrifying motor systems in road transportation, a pivotal step towards enhancing environmental friendliness. Notably, the surge in popularity of electric cars (EVs) over the past five years has marked a substantial shift in the trajectory of future mobility, poised to replace conventional gasoline-powered vehicles. With fewer moving components and the flexibility to harness energy from various sources, electric vehicles offer a compelling edge over traditional gasoline, diesel, and even natural gas-powered counterparts. While the road to widespread EV adoption is not devoid of challenges, a confluence of factors such as the continued surge in renewable energy production, declining battery costs, and breakthroughs in battery technology have collectively paved the way for their promising ascent. Central to this transformative landscape are renewable energy charging stations, vital facilities that facilitate the replenishment of electric vehicle batteries through electricity harnessed from sustainable sources like solar, wind, hydro, and geothermal power. As a vital nexus in the ecosystem of electric mobility, these stations embody the convergence of clean energy and transportation. Their role is pivotal in extending the reach and viability of electric vehicles, helping to alleviate range anxiety and fostering greater confidence among consumers to embrace EVs as a feasible and sustainable mode of transportation. In this context, understanding and optimizing the deployment and operation of renewable energy charging stations emerge as critical imperatives, aligning with the broader goals of reducing carbon emissions and promoting eco-

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friendly practices.

These charging stations can be located in various places, such as public parking lots, residential areas, commercial buildings, and highways [1]. The mobile charging station is not meant to replace the fixed charging station but rather to supplement it, particularly in locations with few or no fixed charging stations. Additionally, in nations with outdated electricity grid facilities, a mobile charging station could handle the increased electricity demand brought on by the market penetration of electric vehicles until enough fixed stations are installed, and the network that distributes electricity infrastructure is modernized. The mobile charging station supports the fixed station in the early stages of infrastructure building. Renewable energy charging stations are essential to the shift towards a more sustainable transportation system. They enable EV owners to charge their vehicles using renewable energy, reducing their carbon footprint and helping to mitigate climate change. By using renewable energy, these charging stations also help to reduce dependence on fossil fuels and promote energy independence. For example, when the supply is inadequate for a station's demand, the mobile renewable energy charging station (MRECS) can remedy the part exceeding the capacity, shown in Fig. 1. Besides, mobile charging stations' service targets are not limited to EVs. They can apply to many other practical applications. For instance, one application close to recent affairs is the ice rain in Montreal. Many regions have a power cut; such charging stations can also provide emergency electricity for areas in urgent need. Perhaps, they are requisites as part of the future of urban infrastructure (see Fig. 1). Due to the variability of the over-dispersed data, load forecasting is unclear. Other investigations addressed the need for EV mobile renewable energy charging stations in terms of space and time. Currently, improvements in machine learning and deep learning approaches help to model the variation in MRECS demands. Machine learning techniques offer a potential remedy for the massive volume of charging data that has resulted from the global adoption of EVs at an accelerated capacity rate.

Mobile renewable energy charging stations with machine learning techniques and accelerated rates have the potential to provide a sustainable, efficient, and accessible solution to charging devices and vehicles [2]. Various techniques, including support vector machines (SVM), are utilized to predict EV charging demand. Machine learning algorithms can analyze population density, traffic patterns, and electricity demand data to identify the most optimal locations for charging stations. This can maximize the charging infrastructure utilization and ensure that stations are located where they are most needed. However, further study is still needed on the interactions between the stochastic generated by EVs and the electricity produced by nearby renewable energy providers. [3] examines the unpredictability of EVs and renewable energy sources. Analogously, the capacities of fixed charging stations can be considered stochastic parameters in the practical use of EVs; there are some potential reasons, such as the charging station's insufficient voltage, equipment maintenance, and the surrounding spaces being partially occupied. The main contributions of the study can be summarized as follows:

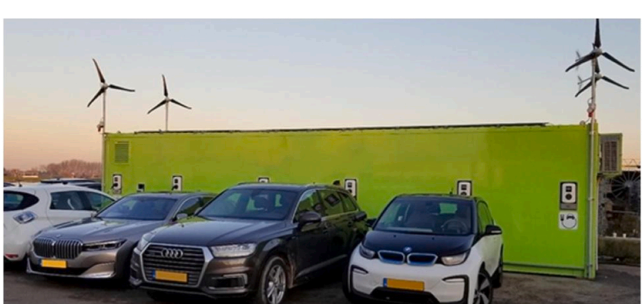

Fig. 1. Sample picture of mobile renewable energy charging station.

- ➢ Presenting two algorithms, DE and DEQL algorithms, that makes utilized to handle uncertainties in renewable energy systems through a stochastic search process and are capable of adapting to changing environmental conditions.
- ➢ Using renewable energy sources in the design of mobile energy stations to integrate into the facilities' operation and how it affects their optimal locations.
- ➢ Proposing two-stage stochastic programming and scenario-based optimization to make decisions robust against unpredictable factors.
- ➢ Introducing approaches to optimize the allocation of these capacities across multiple locations to efficiently meet the changing energy demands and minimize emissions and costs.

The remaining article is organized as follows. Literature review of models and relative applications in Section 2, introduce the problem to solve and mathematical models in Section 3. Section 4 addressee two main solution approaches in this research. Section 5 discuss the computational experiment and sensitivity analysis based on a realistic area of downtown Shanghai. Section 6 present about the main discussion and limitations of this research. Lastly, the conclusion and future research directions provide in Section 7.

2. Literature and related works

In recent years, promoting electric vehicles (EVs) as a viable alternative to conventional vehicles powered by combustion engines is one of the most efficient ways to address the issues of fossil fuel scarcity and ecological pollution. Increasing EV use is expected to significantly influence the grid, according to analyses assessing current networks and forecasting future integration implications. The regional goals, legislative aims, and the acceptance level of EVs all influence the demand for EV charging stations. This indicates that the demand for EV charging stations is more lucrative in areas where EV adoption is high. According to the results of [4] investigation into two decisions (location and route) with time windows, more effective service is required to boost battery capacity or enhance charging rates. [5] found comparable outcomes when they modeled a mobile charging facility's routing issue as an optimization problem with time windows. [6] developed a computational framework that reduces the overall investment cost by considering several variables when determining the position of permanent charging stations, such as driving habits, requests for charging stations, road design, permanent development expenses, and operational costs. Machine learning methods can help to optimize the performance, efficiency, and sustainability of renewable energy charging systems, making them more effective and accessible to consumers [7]. Artificial neural networks, support vector machines, and deep learning are examples of artificial intelligence (AI) techniques. The adoption of artificial neural network (ANN) techniques in load forecasting had become a popular research area before the turn of the twenty-first century because of their flexible solid, autonomous, and adaptable abilities.

The energy usage prediction is a multiple regression issue to forecast the amount of energy the PEV client will require after plugging in [8]. It is then subjected to numerous mathematical machines learning regression algorithms. A data set from Canadian public charging stations validate this methodology. Applications of AI are becoming more prevalent in the supply chain forecasting [9]. An application of AI that could have a significant long-term impact is accelerating the expansion of green, environmentally friendly electricity generation through an ideal energy storage situation. The power sector and the energy industry change may benefit more from AI in various contemporary energy technologies, such as deep learning, machine learning, and sophisticated neural networks. The amount of renewable energy adoption with energy storage is assessed by [10]. According to their research estimate, renewable energy sources may reach 75% of the grid. By considering renewable energy data, [11] determined an ML model to enhance the EV consumption model. They also provided a wide range of accurate and novel literature on the energy optimization performance of smart grid components. Utilizing computational optimization algorithms in this domain also opens up new perspectives in terms of energy efficiency.

Researchers have been interested in combining location models with stochastic programming methods in recent decades. The study focused [12] on the challenge of identifying optimal locations for biomass facilities, driven by the geographic spread of biomass materials. It introduces a GIS-MCDA approach enhanced with Weighted Linear Combination (WLC) and sensitivity analysis to determine suitable areas for biomass facility placement. This approach has broader implications, as it offers a means to address renewable energy planning within a sustainable environmental context [13]. The research suggests the potential for its proposed approach to inform decision-making processes related to renewable energy management policy in diverse sectors, including governmental and industrial domains. In contrast, our study delves into the critical role of mobile renewable energy charging stations in promoting electric vehicle adoption and reducing fossil fuel reliance [14].

In this paper, a two-stage stochastic programming problem or stochastic programming with recourse by [15] will be used to reformulate the location problem. Other remarkable works, including [16] and [17], modify the incapacitated facility location with stochastic variables, including the customer's demand, the unit cost of satisfying the customer from a specific location, and the fixed cost of locating at the candidate location. [18] assumes the customer's demand is stochastic for the capacitated facility location problem. [19] studies, the number of opening facilities is uncertain. For improving customer service, based on initial opening facilities, [20] allows increasing new opening facilities depending on the customer's demand, whereas [21] is the opposite of the previous article, existing facilities have to be closed, where [22] considers the covering-type location problems under demand uncertainties [23]. Moreover, [24] are overviews of facility location problems with uncertainty.

Emerging as the times require, applications of relocatable facilities have the benefits of adapting to the times to optimize the cost and meet different needs. Many multifarious applications have been studied for relocatable facilities. [25,26] study location optimization problems for mobile vendors or food trucks in interurban environments to serve more customers. [27] focuses on allocating police routine patrol vehicles on the city streets to improve public security. [28] investigates practical problems for the bike-sharing system: there is only an available bike for renting and capacitated stations with an empty spot for returning at rush hour. The article provides a solution to the dynamical model to balance the inventory of unused bikes among stations with adequate inventory and short inventory. [29] also lies their research on temporarily locating transportable charging stations for the electric vehicle, but under constraints with deterministic charging demands. [30] interrelates to the distribution problem of optimization. Finally, the unmanned market on wheels for stall economy has been a state-of-the-art application in recent years. [31] emphasizes planning routes based on the reformative vehicle problem model, and [32] investigates the modified dynamic p-median problem under uncertain customer demands based upon robust optimization to locate them in the environment. According to Table 1, the most significant innovation of the present research is designing a new mathematical model for multi-level MRECS application, considering other related works in terms of objectives, solution approaches, and performance. Also, considering local search-based and random-based discovery, which were not available in earlier iterations of the established ML-Stochastic methods given in this study, has substantially enhanced the efficiency of the renewable charging stations.

According to the authors, the existing research on MRECS needs a thorough investigation into the various benefits of technology, environment, and finance within a multi-objective two-stage stochastic model while incorporating machine learning techniques. The significant gaps in the current literature can be summarized as follows:

Table 1
The review of various methods based on the energy charging station location topic.

Authors	Objectives			Time period		Methodology				Uncertainty		Application				Solution approaches		
	Cost	Location	Environment	Single	Multiple	MILP	Fuzzy analysis	Stochastic	Robust optimization	Yes	No	Numerical example	Case study	Multi-echelon	Sustainability	Artificial Intelligence	Heuristic	Decision-making
Wang et al. [33]		*			*	*			*		*	*		*				*
Shadnam Zarbil et al. [34]	*		*		*		*	*		*		*	*				*	*
Momenitabar et al. [35]		*		*		*	*			*		*		*		*		
Liu et al. [36]		*	*		*			*	*		*	*		*			*	
Liang et al. [37]		*				*			*		*	*				*		
Ala et al. [38]	*		*		*		*			*			*	*			*	*
Ahmad et al. [39]	*			*		*	*			*			*	*			*	
This research	*	*	*		*	*		*			*	*	*		*	*	*	

- The incorporation of MRECS into the framework in a scenario of significant wind energy access based on the multi-objective approach has not been researched, despite the optimal planning of mobile energy stations in the energy system being assessed from financial, technological, and environmental standpoints.
- MRECS have been applied as stationary sources into energy systems for multiple objectives, and the facility location capability of renewable energy stations in reducing line congestion and minimizing operational costs in the emissions process needs to be addressed.
- Even though in many types of research, different combinations of optimization algorithms with the help of solution approaches were suggested, in this research, considering one of the latest methods of machine learning algorithm, called reinforced learning (Q-Learning), with the help of a Differential Evolutionary (DE) algorithm. Range concern is another gap in the growth of the EV market. An EV's distance diminishes with driving habits, weather, and traffic, necessitating more frequent recharging. Examine the possibilities of vehicle-to-grid (V2G) technology, which enables electric vehicles to use and return energy to the grid. Due to the concept's ability to support unidirectional energy flow, the system's sustainability may be improved.

3. Problem definition

In this research, A set of potential facility locations is denoted by J, and a set of demand points must be serviced, denoted by I. A subset of capacitated facilities with stochastic capacities and fixing costs has to be opened that satisfy each demand point from the (nearest) facilities it takes service from over multiple periods. There are some costs for opening or closing a facility between consecutive periods. The goal is to minimize the total cost overall and reduce emissions. Fig. 1 depicts the overall schematic of the proposed MRECS.

However, the total demand from customers may be greater than the total capacity that all facilities can supply at some periods. Then, capacitated recourse facilities with very high fixing costs can be opened at these periods on potential facility locations to supply extra capacity to guarantee all customer's demands can be satisfied [40]. Again, the goal is to minimize the total cost.

3.1. Mathematic model

The following are the parameters and decision variables for the deterministic model. Assuming that the set of candidate locations and the set of demand nodes can be regarded as a coincidence in this project, which means $|I| = |J|$. Notations used in the model are described as follows:

Sets:

$i \in I$	Index of demand nodes,
$t \in T$	Index of time periods in the planning horizon,
$j \in J$	Index of set of candidate locations,

Parameters:

C_{ij}	unit cost of satisfying customer $i \in I$, $j \in J$,
ω_{it}	The demand of customer $i \in I$, at time period $t \in T$,
f_{jt}	The fixed cost of locating at candidate location $j \in J$ at time period $t \in T$,
q_j	The capacity of a facility located at candidate site $j \in J$,
b_{jt}	The fixed cost of opening or closing a facility at candidate location $j \in J$ at time period t ∈T
f_{jt}	recourse cost of locating recourse facility (mobile charging station) at candidate location j ∈ J at time period t ∈ T,
p_s	The probability of scenario s ∈ S happens,
M	a constant to guarantee the priority of primary facilities,
Q	The capacity of the recourse facility,
q_j^s	The stochastic capacity of a primary facility located at candidate location j ∈ J of scenario s ∈ S,

Decision variables:

$x_{i,j,t}$	fraction of the demand of customer i ∈ I that is supplied from facility j ∈ J at time period t ∈ T,
y_{jt}	binary variable that is 1 if a facility is located at candidate location j ∈ J at time period t ∈ T, and equals 0 otherwise
u_{jt}	auxiliary binary variable that is 1 if a new facility is opened at candidate location j ∈ J at the beginning of time period t ∈ T, and equals 0 otherwise,
v_{jt}	auxiliary binary variable that is 1 if an existing facility is closed at candidate location j ∈ J at the beginning of time period t ∈ T, and equals 0 otherwise,
x_{ijt}^s	The fraction of demand of customer i ∈ I that is supplied from primary facility j ∈ J at time period t ∈ T of scenario s ∈ S,
$\underline{x}_{ijt}^s$	fraction of demand of customer i ∈ I that is supplied from recourse facility j ∈ J at time period t ∈ T of scenario s ∈ S,
z_{jt}^s	binary variable that is 1 if a recourse facility is located at candidate location j ∈ J at time period t ∈ T of scenario s ∈ S, and equals 0 otherwise,

The introduced robust possibilistic optimization model for the blood supply chain network with lateral freight can be represented as follows using the above notations:

$$Min \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} c_{ij}x_{ijt} + \sum_{j\in J}\sum_{t\in\{2,..,T\}}\left(a_{jt}u_{jt} + b_{jt}v_{jt}\right) + \sum_{j\in J}\sum_{t\in T} f_{jt}y_{jt} \tag{1}$$

subject to

$$\sum_{j\in J} x_{ijt} = 1 \forall i \in I, t \in T \tag{2}$$

$$x_{ijt} \le y_{jt,} \forall i \in I, j \in J, t \in T \tag{3}$$

$$\sum_{i\in I} \omega_{it}x_{ijt} \le q_j y_{jt,} \forall j \in J, t \in T \tag{4}$$

$$v_{jt} - u_{jt} + y_{jt} - y_j = 0 \forall j \in J, t \in \{2,.,T\} \tag{5}$$

$$v_{jt}, u_{jt}, y_{jt} \in \{0,1\} \forall j \in J, t \in T \tag{6}$$

$$x_{ijt} \ge 0 \forall i \in I, j \in J, t \in T \tag{7}$$

The first objective function in Eq.(1) is minimize the cost where constraint (2) ensures the demand of all customers over the time horizon must be satisfied, constraint (3) shows the customer can assign its demand to the facility only if it is open, constraint (4) ensures consumers cannot assign excessive demands to a facility if over its capacity, constraint (5) relates to opening and closing costs, constraint (6) is the binary constraint, and constraint (7) is the non-negativity constraint.

Suppose the overall requests from consumers exceed the total capacity of the facilities at some points. In that case, neither constraint (2) nor constraint (4) can be met, and the Section 3.1 model cannot develop a workable solution. It is necessary to implement the two-stage stochastic framework that includes recourse; as a result, to prevent impossibility.

3.1.1. Developed two—step stochastic model

The energy landscape is subject to fluctuations in demand, supply, and renewable resource availability. By adopting stochastic programming, we can account for these uncertainties in capacity, demand, and other relevant factors that impact the decision-making process. This approach enables us to develop more robust and adaptable solutions that consider multiple scenarios and mitigate risks associated with variability. While MILP and LP models are suitable for deterministic problems, they may not fully capture the complexities and dynamic nature of energy facility deployment, especially when addressing sustainability goals and accommodating real-world uncertainties. Stochastic programming offers a more comprehensive approach that aligns with the dynamic and uncertain nature of energy systems, making it a pertinent choice for our study's focus on mobile renewable energy charging stations and their sustainable deployment. The genetic form of the linear programming model parameterized by the random vector (ω), as follows:

$$Min \sum_{j\in J}\sum_{t\in\{2,.T\}}\left(b_{jt}u_{jt}+b_{jt}v_{jt}\right)+\sum_{j\in J}\sum_{t\in T}f_{jt}y_{jt}+\sum_{s\in S}p_s\left(\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}c_{ij}x^s_{ijt}+\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}Mc_{ij}\overline{x}^s_{ijt}+\sum_{j\in J}\sum_{t\in T}\overline{f}_{jt}z^s_{jt}\right) \tag{8}$$

S.t

$$\sum_{j\in J}\left(x^s_{ijt}+\overline{x}^s_{ijt}\right)=1\forall i\in I,t\in T,s\in S \tag{9}$$

$$x^s_{ijt}\le y_{jt}\forall i\in I,j\in J,t\in T,s\in S \tag{10}$$

$$\overline{x}^s_{ijt}\le z^s_{jt}\forall i\in I,j\in J,t\in T,s\in S \tag{11}$$

$$\sum_{i\in I}\omega_{it}x^s_{ijt}\le q^s_j y_{jt}\forall j\in J,t\in T,s\in S \tag{12}$$

$$\sum_{i\in I}\omega_{it}\overline{x}^s_{ijt}\le Qz^s_{jt}\forall j\in J,t\in T,s\in S \tag{13}$$

$$v_{jt}-u_{jt}+y_{jt}-y_j=0\forall j\in J,t\in\left\{2,.,T\right\} \tag{14}$$

$$z^s_{jt}\in\left\{0,1\right\}\forall j\in J,t\in T,s\in S \tag{15}$$

$$v_{jt},u_{jt},y_{jt}\in\left\{0,1\right\}\forall j\in J,t\in T \tag{16}$$

$$x^s_{jt},\overline{x}^s_{jt}\ge 0\forall i\in I,j\in J,t\in T,s\in S \tag{17}$$

Where constraint (9) ensures that the demand of all customers over the time horizon must be satisfied by either primary or recourse facilities for all scenarios, constraints (10) and (11) show customers can only assign to facilities only if they are open for all scenarios, constraints (12) and (13) ensure customers cannot assign excessive demands to a facility if, over its capacity for all scenarios, constraint (14) relates to opening and closing costs, constraints (15) and (16) are binary constraints, and constraint (17) is the non-negativity constraint.

4. Solution approaches

This section describes the approaches used to mitigate the suggested model. This study applied a hybrid algorithm approach based on optimization and machine learning algorithms.

4.1. Differential evolutionary algorithm

In this research, the section employs the differential evolution (DE) algorithm, an evolutionary algorithm for solving global optimization problems by iteratively improving a candidate solution based on an evolutionary process. DE was introduced by [41]. The main idea behind the DE algorithm is to iteratively improve a population of candidate solutions to find the optimal solution to a given optimization problem. The algorithm starts by randomly initializing a population of potential solutions, often called individuals or agents. Each individual in the population represents a potential solution to the problem. One of the advantages of the DE algorithm is its simplicity and ease of implementation. It does not require derivative information, making it applicable to many optimization problems. Additionally, DE is effective in solving both continuous and discrete optimization problems and problems with noisy or non-linear objective functions.

In the following, we will examine the flowchart and pseudo-code steps in Fig. 2 of the algorithm in full. Please note that this pseudo-code of the Differential Evolution algorithm. The implementation details, such as the fitness evaluation function and termination criteria, may vary depending on the specific problem being solved.

The flowchart provided in Fig. 3a visual representation of the steps involved in the DE algorithm, making it easier to understand and implement the algorithm in practice.

4.2. Q-Learning method

Fig. 4 shows the basic framework of Reinforcement Learning (RL) where an agent observes its environment and receives a reward or penalty for certain actions. The agent aims to learn a policy that maximizes the cumulative reward over time. At each time step t, the agent is in one of the possible states St of the environment and chooses an action at from the set of possible actions A(St) available in that state. When the agent takes this action, it receives an immediate reward rt and transitions to a new state St+ 1. The process then repeats, with the agent choosing an action in the new state based on the reward it received and its current state. The agent learns the optimum policy through trial and error by taking action and receiving feedback through rewards and penalties.

Q-learning is a specific algorithm for finding an optimal policy in a given environment. At the same time, RL is the more general process of training an agent to interact with an environment to maximize a reward signal [41]. In Q-learning, the agent learns an action-value function, also known as a Q-function, which estimates the expected return of a certain

Generate the initial population of individuals

Do

For *each individual j in the population*

Choose *three numbers x_1, x_2 and x_3 that is,* $1\le x_0,x_1,x_2\le N$ *with* $x_0\ne x_1\ne x_2$

Generate *a random integer* i_{rand} *€ (1, N)*

For *each parameter i*

$$v_{i,g}=x_{r,g}+F(x_{r1,g}-x_{r2,g})$$

$$u_{i,g}=u_{i,j,g}\{v_{j,i,g}\ \text{if}\left(rand_j(0,1)\le j=j_{rand}\right)$$

$$\text{Otherwise}\ x_{i,j,g}$$

End For

Replace $x_{i,j,g}$ *with the child if* $x_{j,g}$ *is better*

End For

Until the termination condition is achieved

Fig. 2. The Pseudo code of DE algorithm.

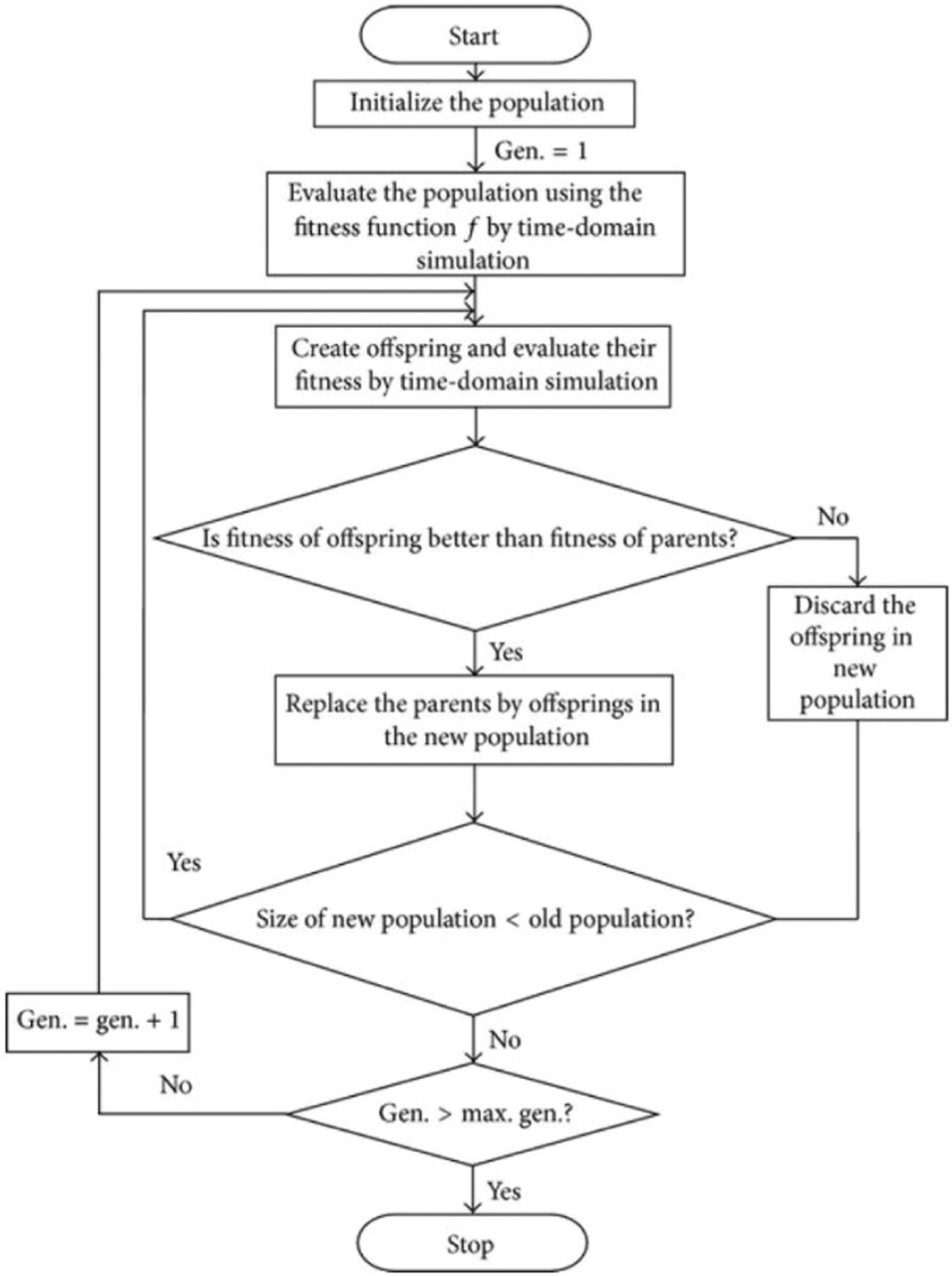

Fig. 3. Flowchart for the normal DE algorithm.

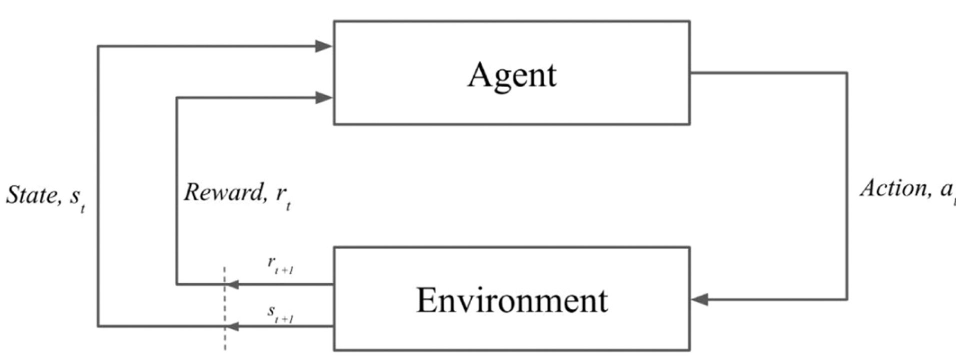

Fig. 4. The flowchart of Reinforcement Learning framework.

action in a certain state. The agent uses a Q-function to determine the best action in each state by selecting the action with the highest Q-value. The Q learning algorithm is off-policy, meaning the agent learns about the optimal policy while following a different, possibly suboptimal policy. This allows the agent to explore the state space and try different actions to learn more about the environment and improve its policy. The Q-function is updated using the Bellman Eq. (18), which states that the value of a state is equal to the expected reward for taking action in that state plus the value of the following state that the agent will transition to the Q-function can be updated using the following equation.

$$Q(s,a) \leftarrow Q(s,a) + a[R + \gamma . \max Q(s',a') - Q(s,a)] \tag{18}$$

Where s is the current state, a is the action taken in that state, α is the learning rate, R is the reward received for taking action a in state s, γ is the discount factor which determines the importance of future rewards, with a higher discount factor implying that future rewards are more important. s′ and a′ are the state and action taken in the next state, respectively. The agent maintains a Q-table containing estimates of the "quality" of each action in each state, known as the action value. The action value of an action is the expected sum of all future rewards that the agent will receive if it takes that action in the current state. The agent aims to learn the action values for all states and actions to choose the actions with the highest action values, thus maximizing the total reward it receives over time. When the agent chooses an action, it receives an immediate reward associated with that action [42]. This immediate reward is used to update the action value of the chosen action in the current state using the Q-learning update rule. The update rule considers the immediate reward and the action values of the possible actions in the new state that the agent will transition to due to its action. This is because the new state may be closer to states with high rewards, so the action values of the possible actions in the new state may be higher. By updating the action values in this way, the agent can learn which actions will likely lead to high rewards and adjust its behavior accordingly. Suppose the agent always chooses the action with the highest action value (a greedy approach). In that case, it will follow a policy likely to lead to a locally optimal solution rather than a global one. This is because the agent will only consider an action's immediate reward rather than its actions' long-term consequences. The Q-learning algorithm often allows the agent to choose random exploratory actions with probability ϵ in each action to overcome this problem which is not necessarily the action with the highest action values. With this strategy, the agent may better understand its surroundings and recognize behaviors that fail to immediately produce the maximum rewards but ultimately result in close to the ideal policy. By exploring different actions and states, the agent can learn more about its environment and find a better overall policy. Fig. 5 demonstrates the general steps of the Q-learning algorithm.

As demonstrated by [43], applying a consistent reinforcement learning (RL) strategy to various other meta-heuristic algorithms establishes the enhanced robustness of combining RL methodologies like Q-learning with DE. This amalgamation results in improved averages and reduced standard deviation across outcomes. Therefore, based on these findings, we opt to not only utilize DE independently but also explore its integration with the Q-learning algorithm within the scope of this study.

5. Computational results

5.1. Data collection

This section provides the results of the described case study. They are obtained with Optimization problems are solved by CPLEX v.10 on an Intel Core i5 (2.6 GHz) 8 GB of RAM processor. In scientific tests, fixed charging stations are considered main facilities, while mobile charging stations are considered backup facilities in the probabilistic model. If the total demands exceed the capacities of fixed charging stations during certain time periods, mobile charging stations will be positioned at potential sites to offer additional charging units. This ensures that all customers can receive the necessary service. The unit cost of links (i, j) to use Euclidean distance measurement.

$$c_{ij} = \sqrt{(loc_{xi} - loc_{xj})^2 + (loc_{yi} - loc_{yj})^2}.$$

To locate the distance between two candidate locations in the coordinate set in Fig. 5. All investigations with $|T| = 7$ days and five same probability scenarios. The permanent cost for extending a selected charging station $f_{jt} = 100$ and a mobile charging station $\bar{f}_{jt} = 1000$ for every period. The commencement cost for extending a new fixed charging station $a_{jt} = 15$, and the ending cost for closing an existing fixed charging station $b_{jt} = 15$. The capacity for each mobile charging station Q = 10 and the constant M= 500. The need for each client in each period is random integers between 3 and 6, as follows:

```
Input: Q(s, a)    0                                   ▷ Initial Q-table
α ▲       0                                           ▷ Initial learning rate
γ ▲       0                                           ▷ Initial discount factor
ϵ ▲       1                                           ▷ Initial exploration rate
Define: Action set (A)
Define: State set (S)
Output: Q-table
Initialize: Q(s, a)
        for t = 0 : t = T do
        T is number of episodes
Initialize: s
Choose at, and st from Q if RAND() ≤ ϵ then
at ← random action else
at ← argmaxa Q(S, a)
Observe r_{t+1}, s_{t+1}, st ← st+1
at ← at+1
Q(s, a) ← Q(s, a) + α[R + γ.max Q(s', a') − Q(s, a)] α ← 0.99α
ϵ ← 0.97ϵ
```

Fig. 5. The general steps of the Q-learning algorithm.

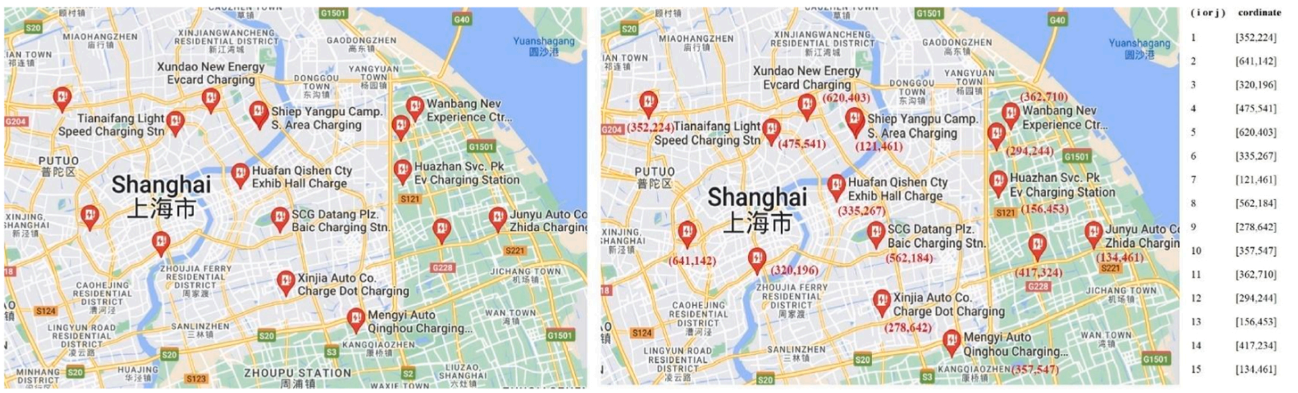

Fig. 6. Locating fixed and mobile renewable energy charging stations in Shanghai.

Table 2
The results of various instances in solution approaches on computing time.

No. Run	DE				DEQL			
	5*5*5	5*5*15	15*15*5	15*15*15	5*5*5	5*5*15	15*15*5	15*15*15
1	293.2	322.6	497.6	617.8	254.4	485.3	299.4	595.4
2	307.4	520.9	740.3	920.4	210.3	353.4	255.8	977.5
3	296.4	407.2	710.2	904.1	195.2	218.6	485.7	756.9
4	290.7	306.5	650.9	863.7	224.7	476.7	847.2	910.5
5	276.5	265.7	239.4	854.2	193.4	195.8	217.7	810.8
6	290.6	345.2	479.5	923.8	285.4	312.7	425.6	845.2
7	310.8	420.4	820.4	959.3	245.4	411.7	760.4	893.4
8	268.4	450.1	578.1	932.6	229.1	347.5	539.4	832.7
9	339.2	437.2	594.2	958.6	325.4	436.7	474.3	924.7
10	305.7	301.4	415.3	685.7	218.6	296.8	396.7	588.7
Average	235.5	315.5	412.7	435.6	226	310.4	325.4	414.2

$$\omega'_{it} = \begin{bmatrix} 3 & 3 & 3 & 5 & 4 & 5 & 5 & 4 & 3 & 4 & 6 & 6 & 5 & 6 & 5 \\ 6 & 6 & 4 & 4 & 4 & 4 & 3 & 4 & 5 & 4 & 4 & 5 & 4 & 6 & 6 \\ 6 & 6 & 4 & 6 & 5 & 6 & 5 & 6 & 6 & 5 & 6 & 6 & 4 & 5 & 4 \\ 5 & 4 & 6 & 5 & 3 & 5 & 3 & 4 & 3 & 3 & 3 & 5 & 4 & 3 & 4 \\ 3 & 3 & 5 & 5 & 4 & 4 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 5 & 5 \\ 3 & 4 & 4 & 3 & 3 & 5 & 3 & 5 & 5 & 6 & 3 & 5 & 6 & 3 & 5 \\ 5 & 3 & 3 & 6 & 4 & 6 & 6 & 5 & 4 & 5 & 5 & 5 & 6 & 3 & 4 \end{bmatrix}$$

Fig. 6 shows fifteen existing fixed charging stations ($|I|=|J|=15$) and specific coordinates in downtown Shanghai based on resources from Google Maps; coordinates in the workspace are collected through Python's OpenCV toolbox.

5.2. Performance analysis algorithms

In this section, the algorithms are thoroughly analyzed, and the standard deviation metric is employed to assess the stability and consistency of algorithms across multiple runs, considering different problem sizes and CPU time. Table 2 presents a summary of the achieved outcomes for the two algorithms. Hence, it shows the DE algorithm has less CPU time than the DEQL algorithm to run a model for various problems. Therefore, in most sizes, the CPU time of each algorithm is shown with a round of ten counts.

Additionally, based on the findings, the algorithms are comparable when taking into account the RPD and RDI metrics [44] from Tables 3,4. As can be observed, DEQL typically achieves less RPD. The RDI ratios of DE, however, are less than DEQL. The findings demonstrate that DEQL is more resilient than DE. Also, the DEQL has less standard deviation for various computation instances than DE, and its computed solutions have less fluctuation than DE. The algorithms' CPU times are highly competitive as well. DEQL, on the other hand, handles most issues more quickly.

In this section, the comparison of the two algorithms regarding the results of the CPU time of size of the problem can be accessed by default and the schematic results of one measure include in RDI for two algorithms is illustrated in the Figs. 7 and 8 respectively below.

In Fig. 7 illustrated when number of size problems based on various executive time increased based on results is obtained from Table 2, DEQL algorithm has outperform than DE algorithm to solve most problems in less amount of time. Moreover, in Fig. 8 we consider one of metric measure RPI rather than other metric because this shows better and robust results in various size problems for two algorithms. Based on results from Table 4 we have concluded DEQL algorithms has shown a robust and better performed in many of problem size with considering average RDI time. Additionally, Fig. 9 displays the boxplot for every achievement metric. As can be observed, for all steps other than the median RPD, the DEQL boxplots are less than the DE boxplots.

To explain why DEQL outperforms DE in this problem, we initially conduct a normality test on the outcomes generated by these algorithms for a large dataset, as illustrated in Fig. 10. It can be observed from Fig. 10 that the results of both algorithms follow a normal distribution. Subsequently, we proceed to employ a two-sample t-test.

μ_1: DE; μ_2: DEQL.

Null hypothesis H_0: $\mu_1 - \mu_2 = 0$.

Alternative hypothesisH_1: $\mu_1 - \mu_2 > 0$.

T-Value	DF	P-Value
6.16	13	0.000

The outcome of the two-sample t-test reveals an extremely low p-value, approaching zero. This outcome indicates a statistically significant distinction between the results obtained from DE and DEQL.

Table 3
The computational results of the metaheuristic algorithms.

Algorithms	Min.	RDI	RPD	STDEV
DE	193.41	0.515	0.211	28.6
DEQL	268.14	0.340	0.140	20.3

Table 4
The investigation of the effect RDI parameters on problem-solving of various sizes.

No. Run	DE - RDI				DEQL - RDI			
	5 * 5 * 5	5 * 5 * 15	15 * 15 * 5	15 * 15 * 15	5 * 5 * 5	5 * 5 * 15	15 * 15 * 5	15 * 15 * 15
1	0.786	0.710	0.500	0.231	0.350	0.359	0.179	0.342
2	0.220	0.728	0.202	1	0.545	0	0.244	0.145
3	0.032	1	0.365	0.487	0.391	0.282	0.024	0
4	0.402	0	0.645	0.894	0.321	0.258	0.403	0.758
5	0	0.902	0.335	0.525	0.120	0.083	0	0.750
6	0.830	0.680	0.835	0.750	0.313	0.475	0.710	1
7	0.972	0.778	1	0.158	0.105	0.855	0.123	0.510
8	0.468	0.450	0	0	0	1	1	0.087
9	0.479	4.123	0.995	0.221	1	0.440	0.162	0.940
10	1	0.925	0.815	0.418	0.530	0.256	0.230	0.595

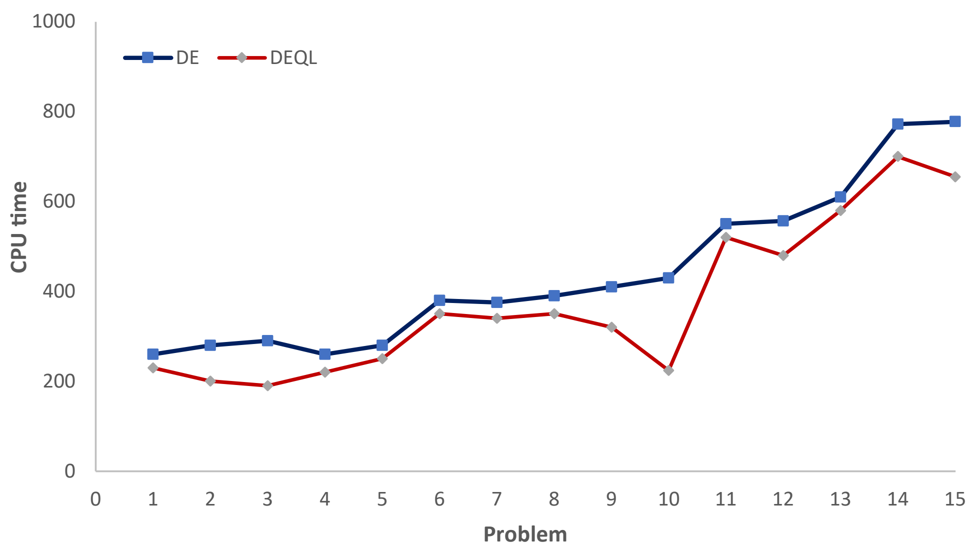

Fig. 7. The average CPU time of metaheuristics for the test examples.

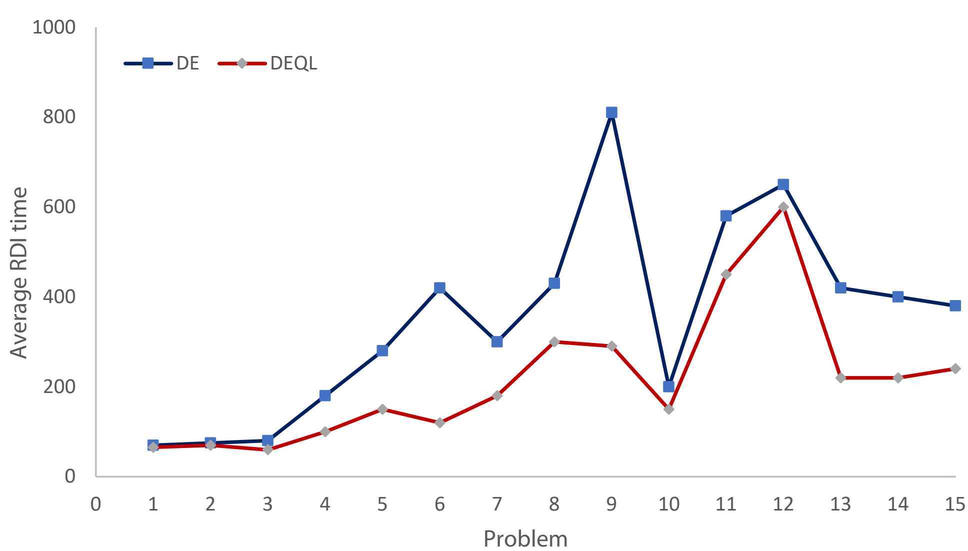

Fig. 8. The average RDI time of two algorithms for the test examples.

Evidently, DEQL demonstrates significantly superior performance in comparison to DE, as supported by these findings. This substantiates the rationale behind the adoption and favorable performance of the DEQL algorithm.

The plot in Fig. 11 illustrates the residual vs. fitted values for a large dataset of DE and DEQL. This plot distinctly demonstrates that the deviation of random results in DE is considerably greater than that in DEQL. This difference is noticeable even without the need for conducting any statistical tests. Therefore, when using the standard deviation as a comparative metric between these two algorithms, it becomes

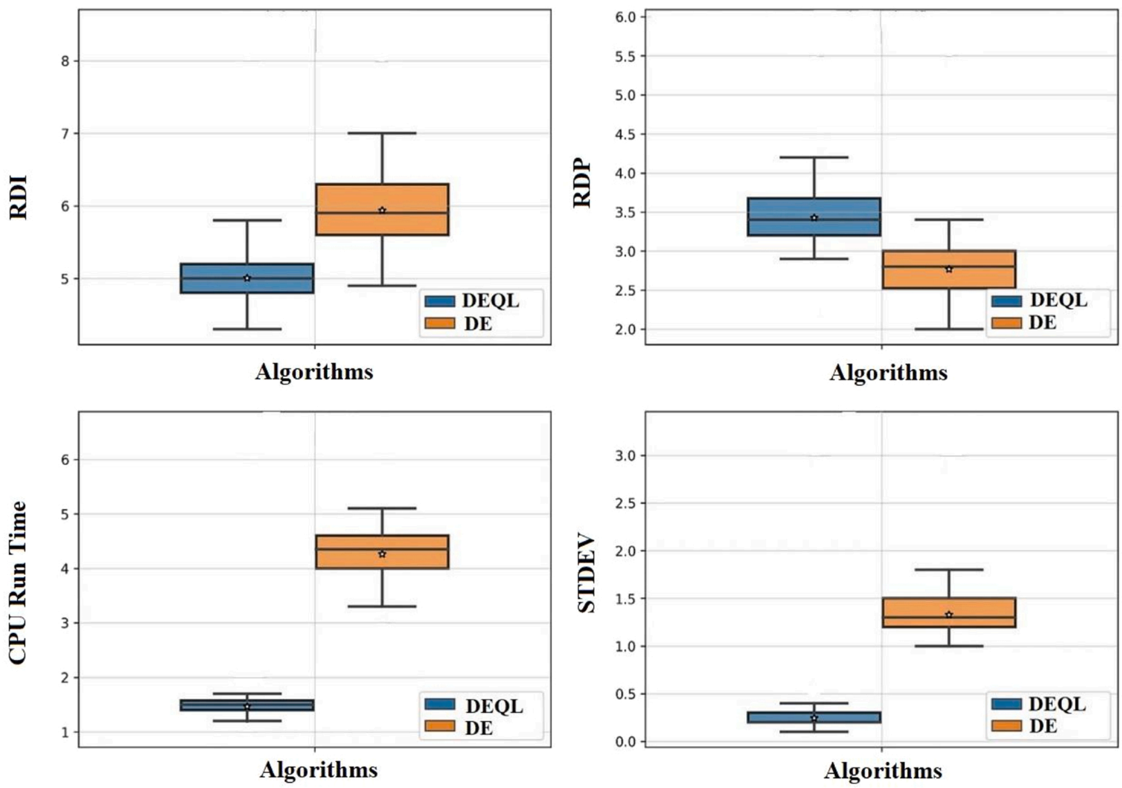

Fig. 9. The boxplots for performance indicators of different metrics for two algorithms.

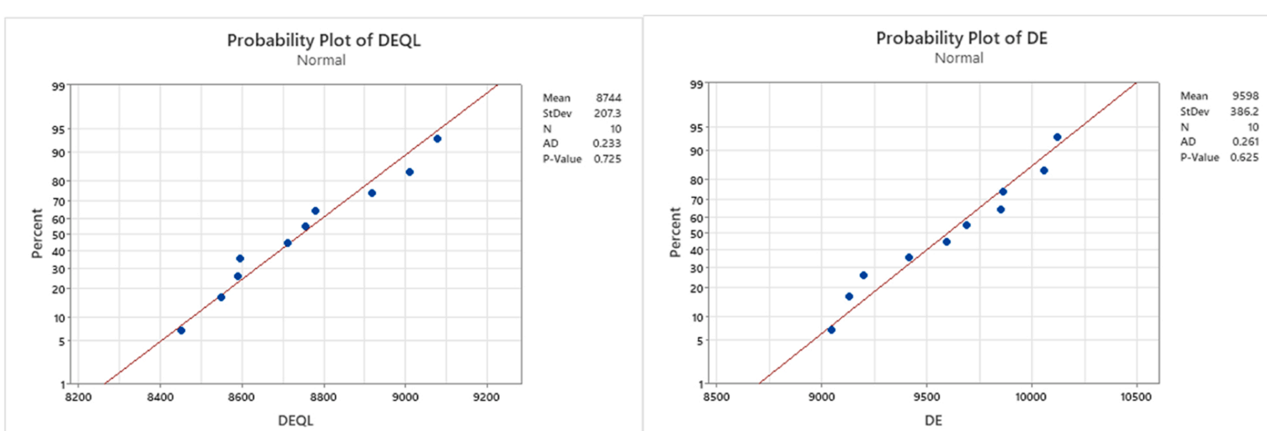

Fig. 10. The normal probability plots for large size of DE and DEQL.

evident that DEQL outperforms DE.

5.3. Sensitivity analysis

In this part, a systematic strategy tries to give executives a deeper understanding of the system by considering the variation of the parameters. The final phase involves a sensitivity analysis to determine the effects of changing the location as one of the critical characteristics of the cost factors of the energy station system. The first experiment considers five same probability scenarios, where s ∈ {1,., 5}. Four of them give median $\widehat{q}^s = 7$that these scenarios can completely meet all customers' demands since $\widehat{q}^s - 1 \geq \max\{\omega_{it}\}$for all s ∈ {1, 2, 4, 5}. Moreover, $\widehat{q}^3 = 3$means demands may sometimes exceed facilities' capacities. Here are five scenarios of capacities for fixed charging stations.

$$\left(q_j^s\right)' = \begin{bmatrix} 6 & 6 & 7 & 8 & 6 & 8 & 8 & 6 & 6 & 6 & 8 & 7 & 6 & 7 & 6 \\ 7 & 7 & 8 & 7 & 7 & 8 & 6 & 6 & 6 & 7 & 7 & 6 & 6 & 8 & 8 \\ 3 & 3 & 3 & 3 & 3 & 5 & 5 & 4 & 4 & 4 & 5 & 5 & 4 & 3 & 5 \\ 6 & 8 & 8 & 6 & 7 & 8 & 8 & 6 & 6 & 8 & 7 & 7 & 6 & 8 & 6 \\ 7 & 6 & 8 & 7 & 6 & 6 & 7 & 6 & 8 & 6 & 7 & 6 & 7 & 8 & 7 \end{bmatrix}$$

The solver takes 300.2 s to solve this mixed integer linear programming (MILP) with a 0% gap, and the best objective equals 18000.2. The following matrix results from the decision variable of fixed charging stations.

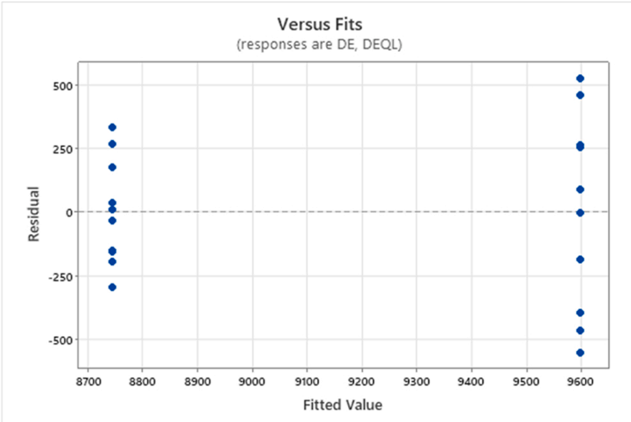

Fig. 11. The residual vs fitted value for large size of DE and DEQL.

$$y'_{jt} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \end{bmatrix}$$

Fixed charging stations 10 and 14 are closed for some periods. Demands at demand point 10 are assigned to either fixed charging station 11 or mobile charging stations during closing periods, and demands at demand point 14 are assigned to either fixed charging station 15 or mobile charging stations during closing periods.

By reducing costs in renewable energy charging stations, sustainability goals can be achieved by making clean energy more accessible, economically viable, and environmentally friendly. The cost of operating rises as carbon emissions are decreased. The theory shows that the provider must cause higher operational costs to reduce carbon emissions. Iteration 16 is the best answer between Pareto's solutions without using fixed costs. It can be seen that location in the amount of $84269.3, which results in a 6.5% decrease in cost and carbon emissions, provides the highest level of sustainability. Fig. 12 illustrate the details of Pareto archived results with considering cost effects.

6. Discussions

The concept of Renewable Energy Integration involves utilizing renewable energy sources like solar, wind, hydro, and geothermal power to charge EVs through strategically placed renewable energy charging stations. These stations are strategically located in various settings, including public parking lots, residential areas, commercial buildings, and highways. In comparison to other methods of renewable energy utilization, we emphasize the effectiveness of this integration. The effectiveness of incorporating renewable energy into EV charging stations is underscored by several key aspects. Firstly, this approach significantly reduces the carbon footprint and environmental impact of the transportation sector. By harnessing electricity generated from renewable sources such as solar or wind, the emissions associated with EVs are considerably lowered. This stands in contrast to conventional vehicles that rely on fossil fuels, which emit higher levels of greenhouse gases, thereby aiding in the mitigation of climate change.

Furthermore, the notion of flexibility and mobility is integral to this integration strategy. We introduce the concept of MRECS that can address fluctuations in supply and demand. These mobile stations offer a solution when fixed charging infrastructure falls short, presenting a dynamic and adaptable option for EV charging that outperforms conventional stationary stations. Our model also posits the potential for mobile charging stations to serve as emergency power sources in critical situations such as power outages caused by events like ice storms. This multifunctional aspect enhances the overall utility and effectiveness of the renewable energy integration approach, showcasing its broader societal benefits beyond just EV charging.

Additionally, we employ machine learning techniques to optimize the placement of charging stations. These algorithms consider factors like population density, traffic patterns, and electricity demand data to identify optimal charging station locations. This optimization strategy ensures maximum utilization of the charging infrastructure, placing stations precisely where they are most needed. This not only enhances efficiency but also underscores the adaptability of the integration approach.

The study presented in this article addresses the dynamic capacitated facility location problem in mobile renewable energy charging stations from a sustainability perspective. The findings of this study provide valuable insights into the optimal placement of mobile charging stations in a dynamic environment while considering capacity constraints and sustainability factors. By formulating the problem as a dynamic capacitated facility location problem, the study offers a comprehensive

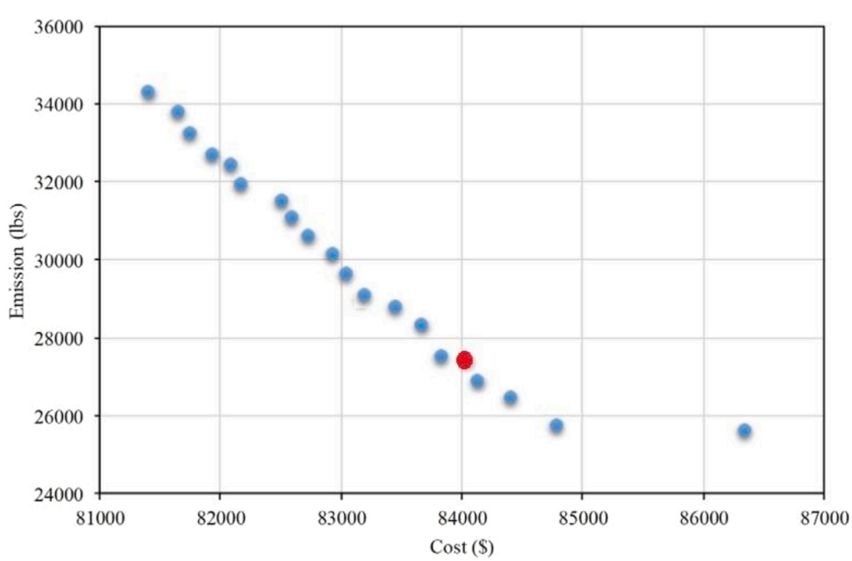

Fig. 12. Pareto's optimal optimization method with fixed cost and emission.

approach to ensuring efficient and sustainable charging stations. One important finding is that incorporating renewable energy sources in charging stations can contribute significantly to sustainability goals. By leveraging renewable energy, such as solar or wind power, the reliance on fossil fuels for electricity generation can be reduced, leading to lower greenhouse gas emissions and a decreased carbon footprint. This finding aligns with the global trend toward transitioning to cleaner energy sources and reducing the environmental impact of transportation. The research also sheds light on the potential economic benefits of reducing costs in renewable energy charging stations. By implementing strategies such as economies of scale, technological advancements, smart grid integration, and operational efficiency, the overall costs of charging infrastructure can be minimized. This cost reduction not only improves the feasibility and financial viability of renewable energy charging stations but also encourages their widespread deployment and utilization. However, it is important to acknowledge the limitations of this study.

The use of Q-learning, a machine learning algorithm, to dynamically fine-tune control parameters in the DEQL presents several advantages and disadvantages. Q-learning's adaptability to changing environments allows DEQL to adjust control parameters based on the optimization problem, potentially improving convergence and performance. Unlike conventional methods, DEQL reduces the need for manual parameter tuning, as Q-learning learns to adjust parameters autonomously. The trained model can generalize its learning to similar problems, expanding DEQL's applicability. This adaptability could lead to faster convergence and more efficient optimization. On the other hand, training Q-learning demands significant computational resources and time, with initial costs potentially outweighing immediate benefits, especially if conventional DE performs well. While generalization is possible, Q-learning might struggle with entirely new problems. Introducing machine learning complexity can hinder understanding, implementation, and debugging. Additional resources might be required during optimization.

To provide a computational complexity comparison between DE and DEQL, it becomes evident upon inspecting the pseudocode of the DE algorithm that the initial "for" loop exhibits a computational order of O (n). In this algorithm, the second "For loop" is nested with one another, and therefore the DE algorithm has an order of O(nˆ2). In proposed DEQL algorithm, the first "For loop" has an order of O(n). In addition, the nested loops have an order of O(nˆ2). In these algorithms, the hybridized Q-leaning part has an order of O(1) which is a constant order. As a result, the proposed hybrid algorithm have an order of O(nˆ2). which is the same as the initial algorithm.

The dynamic capacitated facility location problem addressed in this research assumes certain simplifying assumptions and constraints. These assumptions may not fully capture the complexity and variability of real-world scenarios. Future research should explore more nuanced models that consider factors such as varying energy demands, real-time traffic conditions, and user preferences to provide more accurate and realistic solutions. Additionally, the study primarily focuses on the location problem of charging stations and does not extensively address other important aspects of sustainability, such as life cycle assessment, social impact, or policy implications.

6.1. Managerial implications

A thorough discussion of limitations and potential managerial implementations is essential to ensure the research's practical relevance and applicability in the context of the Capacitated Facility Location Problem to Create plans for gathering and analysing current information on consumer demand, transportation patterns, and the availability of renewable energy sources. To improve data accuracy and enable informed decision-making, implement IoT devices and data analytics technologies. Work with stakeholders and energy providers to ensure effective integration of renewable energy sources. To optimize energy generation, archiving, and consumption, implement smart energy management systems.

7. Conclusions and future directions

The deployment of mobile renewable energy charging stations is pivotal for advancing the widespread adoption of electric vehicles and diminishing dependence on fossil fuels. This study contributes to the discourse by addressing the dynamic capacitated facility location problem within the context of mobile charging stations, emphasizing the imperative sustainability aspect. Introducing a novel approach, Two-stage stochastic programming with recourse, the paper demonstrates its efficacy in optimizing the operational dynamics of mobile renewable energy charging stations. The proposed algorithm not only addresses the complex nature of the problem but also provides a strategic perspective for deploying these stations efficiently. This research not only enhances our understanding of the operational challenges but also presents viable solutions that align with the broader goal of sustainable transportation solutions.

This article presents a new functioning mode for a mobile charging station, one that assumes transitory positions in a few potential locations during particular times. The proposed Two-stage stochastic programming with recourse performs well for this application, and the location of MRECS management addressed the complex dynamics of reusable items. Some fixed charging stations were not necessarily needed to keep open if exceptional circumstances happen, such as Experiments, then mobile charging stations could get involved as a backup choice to guarantee that all demand points could be satisfied. For solving the proposed problem, we considered two optimization and RL algorithms called DEQL. In this section, the algorithms were thoroughly examined. The algorithms addressed 15 numerical problems of various sizes. For every developed mathematical example, each algorithm was run ten times. To evaluate and analyze the effectiveness of metaheuristics, we considered several performance metrics, including median RPD, median RDI, median CPU time, and median standard deviation. To assess the quality of the solution, the median RPD and RDI were employed as two relative error metrics. The results indicated that the DEQL could minimize the total operation cost and carbon emission by 7% and 20%, respectively. In contrast, the DE could decrease the total operation cost and carbon emission by 2.5% and 5%, respectively. The analysis of the data leads to the conclusion that the DEQL algorithm consistently outperforms the DE algorithm across various problem sizes and execution times. This superiority is particularly evident when observing an increase in the number of size problems, where the DEQL algorithm solves most problems in less time compared to the DE algorithm. Additionally, the focus on the RPI metric in the analysis provides a clearer understanding of the algorithms' performance across various problem sizes. The results reinforce the conclusion that the DEQL algorithm demonstrates robust and superior performance, particularly when considering the average RDI time. Notably, for all metrics measured in our study except the median RPD, the DEQL consistently show lower values than the DE. This consistent pattern across different metrics and problem sizes reinforces the conclusion that the DEQL algorithm consistently outperforms the DE algorithm.

The future studies directions can be considering a robust optimization addressing Fixed costs in the objective containing uncertainty parameters. Another direction is Incorporating resource limitations and a temporal aspect into the model enhances its realism. Introducing uncertainty to account for variations in travel flows and demand would further align the problem with real-world scenarios. Also, considering uncertainty analysis with fuzzy intervals and extending the work by considering Markov dependence hypothesis.

CRediT authorship contribution statement

Sadeghi Amir Hossein: Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Bani Erfan Amani:** Investigation, Software, Writing – original draft, Writing – review & editing. **Deveci Muhammet:** Supervision, Validation,

Visualization, Writing – review & editing. **Ala Ali:** Conceptualization, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

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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