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Planning of electric vehicle charging stations: An integrated deep learning and queueing theory approach

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A R T I C L E I N F O

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A B S T R A C T

This study presents a hybrid solution for the charging station location-capacity problem. The proposed approach simultaneously determines the location and capacity of charging stations (i.e., number of charging piles), and assigns piles to electric vehicles based on their level of charge. The problem is formulated as a bi-objective mixed-integer nonlinear programming model to minimize the total cost of establishing charging stations together with the average customers' waiting time. The proposed solution combines queueing theory with mathematical modelling to estimate the average waiting time. A deep learning algorithm is then developed to enhance the precision of waiting time estimation. Another contribution is involving a deep neural network model in improving NSGA-II algorithm. Numerical experiments are conducted in Halifax, Canada to assess the performance of the proposed framework. The results demonstrate the strong predictive performance of the deep learning algorithm and highlight the limitations of traditional queueing models in estimating waiting times in charging stations (i.e., 99.8% improvement in computation time, as well as accuracy improvement of time estimations from 13% to 1.6% deviation). Several valuable insights are obtained to improve the operational performance of charging stations such as achieving a significant (i.e., 61.5%) drop in the average waiting time across the network by a modest (i.e., 29.2%) increase in the initial investments. Also, it reveals that the variability of service rate significantly impacts the average waiting time (i.e., a 50% increase in the variability of service rate causes a substantial 950.56% surge in the average waiting time). The findings underscore the need to control service rate fluctuations to reduce wait times and boost driver satisfaction. The improved NSGA-II algorithm shows 12.77% improvement in the Pareto front solutions. Finally, the proposed prioritization strategy based on the charging level of vehicles could reduce the average waiting time and cost compared to the first-come-first-served strategy.

1. Introduction

Transportation contributes to 23 % of global greenhouse gas (GHG) emissions, with road transport accounting for approximately

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70 % (Jaramillo et al., 2022). Governments worldwide are acting to decrease GHG emissions, with ambitious targets and initiatives. For example, the European Commission (EC) seeks a 90 % cut in emissions by 2050 through improved sustainability in transportation (Zhavoronkov and Middell, 2022). Electric vehicles (EVs) are recognized as viable solutions to facilitate the transition towards a greener and more sustainable global economy. Despite the growing prominence of EVs in recent years, the global rate of their adoption remains comparatively low (Wu et al., 2024). Consequently, a significant amount of research is being conducted to explore strategies for accelerating the adoption of EVs. Literature identifies some barriers to wider EV adoption such as high costs, range anxiety, resale concerns, and inadequate infrastructure. Limited charging availability leads to logistical challenges, reducing accessibility and increasing wait time, and amplifying range anxiety (Brückmann and Bernauer, 2023).

Widely available EVs can typically be categorized into three primary groups, namely hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) (Al-Alwash et al., 2024; Crisostomi et al., 2017). BEVs exclusively rely on rechargeable batteries for power and do not require a fuel tank. PHEVs are equipped with both gasoline engines and electric motors to drive the car. HEVs are similar to BEVs in the sense that they only use electrical energy to drive; however, they are not charged using external sources and instead charge their batteries via the power generated by their combustion engine. All types of EVs produce lower levels of emissions than internal combustion engine vehicles (ICEVs); however, BEVs are considered the superior alternative due to a set of justifications such as the lowest noise pollution. Consequently, this paper focuses on BEVs.

Regardless of the discussed advantages of BEVs, certain challenges have limited their production and adoption in the market (Vimal et al., 2024; Crisostomi et al., 2017). For instance, high production costs, limited driving range compared to ICEV, and limited availability of charging stations are considered the main barriers to the widespread adoption of BEVs (Cai et al., 2024; Liao et al., 2019; Schiffer and Walther, 2018). Specifically, studies indicate that the expansion of charging station infrastructure could potentially increase the demand for BEVs by up to 5.5 times their current sales figures (Vimal et al., 2024; Chen et al., 2020; Dong et al., 2014). Among different charging technologies, direct current (DC) allows EVs to be fully charged in 20–30 min (Zeb et al., 2020). Nevertheless, charging EVs using fast charging technology is still much slower than refuelling conventional ICEVs, which can be completed within a few minutes.

As the demand for EVs continues to grow, there is a pressing need to add more charging stations which is in line with a recent study that predicts significant increase in the number of charging piles globally in 2040 (Kchaou Boujelben, 2021).

The charging station location problem (CSLP) searches the optimal location for establishing EV charging stations. Charging station location decisions are strategically important since they involve costly decisions that cannot be reversed easily (Godbersen et al., 2024; Jochem et al., 2016). Consequently, solutions to CSLP should satisfy charging requirements while adhering to budgetary limitations. In general, there are two models to investigate CSLPs. The node-based models consider classical facility location modelling approaches in which the recharging demand originates from road network nodes (Scheiper et al., 2019). In contrast, a more recent stream of research considers flow-based demand and assumes that EV drivers frequently exhaust their batteries and therefore require recharging services while en-route. As a result, the demand for charging stations is modelled based on the aggregation of origin-to-destination journeys undertaken by EV drivers.

Despite advanced charging technology, capacity limitations at charging stations result in lengthy wait times, particularly during peak hours. These extended wait times deter people from adopting EVs. However, the existing literature lacks comprehensive studies that address the impact of charging station wait times, often making restrictive assumptions (Zhang et al., 2023; Chen et al., 2020). Given the significance of wait times and the limited research in this area, this paper aims to explore strategies for mitigating wait times through strategic infrastructure planning. Specifically, the paper proposes a hybrid solution for the charging station location-capacity problem (CSLCP). The proposed approach optimizes both the location and the number of charging stations and assigns them to EVs based on their state of charge (SoC). The problem is formulated as a bi-objective mixed-integer nonlinear programming (MINLP) model. The primary objective is to minimize the total costs of establishing stations and installing charging piles, while the secondary objective is to minimize the average wait time for EVs at charging stations.

The key contributions of this study include: 1) Hybrid solution for CSLCP: This study introduces a novel hybrid solution for CSLCP that, unlike traditional approaches, simultaneously determines the optimal locations and capacities for charging stations, addressing the dynamic nature of charging demand of EVs. 2) Integration of queueing modeling: This paper integrates queueing modeling into a MINLP formulation, allowing for the accurate representation of waiting time at charging stations. This integration enhances the precision of the optimization framework by considering the real-time dynamics of charging processes, ensuring that waiting time is minimized. 3) Deep Neural Network (DNN) for waiting time estimation: A novel aspect of this research lies in the development of a DNN-based approach to enhance the accuracy of waiting time predictions. By leveraging advanced machine learning techniques, the proposed model can more effectively estimate waiting times, especially in scenarios with complex and probabilistic demand patterns (i.e., the case study showed that DNN could reduce the computation time by 99.8 % compared to the queueing theory method. In addition, the accuracy of estimations, on average, improved from 13 % to 1.6 % using the proposed method). This contribution is significantly important because the literature uses queueing theory method to estimate the waiting time. 4) Innovating integration of DNN in NSGA-II algorithm. A heuristic selection operator is introduced that leverages deep learning techniques. The selection operator benefits from a trained neural network to predict the likelihood of choosing parent in chromosomes (i.e., the case study showed that the improved NSGA-II could improve the Pareto front solutions by 12.77 % compared to the standard NSGA-II). This result is significant because in most cases, the integrated time estimation and optimization methods are non-convex and nonlinear, which make the solution approach timely and complex. 5) Innovative line-based strategy: This paper introduces a unique prioritization strategy known as the line-based strategy (i.e., the case study showed that the line-based strategy could reduce the waiting time by 50.3 % compared to the first-come-first-served approach). Unlike the traditional first-come-first-served approach, this strategy optimizes charging station operations by categorizing EVs into separate lines based on their state of charge (SoC). By ensuring that EVs with different SoC levels are not waiting in the same line, the charging process becomes significantly more efficient and tailored to individual vehicle needs.

The contributions of this study collectively provide a powerful tool for the planning and expansion of charging stations, particularly by considering scenarios in which demand and charging rates exhibit probabilistic behavior. By integrating queueing modeling, advanced machine learning, and innovative strategies, the proposed framework addresses critical challenges in optimizing charging station networks, ultimately promoting the widespread adoption of electric vehicles and sustainable transportation solutions. In terms of insights for decision-makers, this study also brings managerial implications for decision-makers. In particular, this study investigates the relative importance of dealing with uncertainty in service rate in charging stations compared to the uncertainty in arrival rate. In addition, the case study shows that with a 30 % increase in investment costs, the total waiting time for EV drivers reduces 2.5 folds.

In the rest of this article, the literature is reviewed, and research gaps are highlighted (Section 2). The studies problem is then explained in Section 3. Section 4 elaborates on the proposed mathematical model. Section 5 presents the developed DNN and improved non-dominated ranking genetic algorithm (NSGA-II). Numerical experiments are conducted and discussed in Section 6. The study is concluded in Section 7 with some future research directions.

2. Literature review

The expected rise in the public EV chargers by 2040 has financial implications. Establishing, relocating, or upgrading EV charging stations, especially fast chargers, necessitates substantial investments. Hence, charging service providers face the challenge of selecting ideal locations within budgetary constraints to meet recharging demand. Consequently, the charging station location problem (CSLP) has gained significant attention in recent years. Insufficient charging infrastructure and long charging processes lead to frequent waiting time for EV charging, underscoring the importance of managing waiting time when selecting charging station locations and capacities. Queuing theory was rarely applied in EV charging station planning (Vijay et al., 2024). Recently, some studies integrated waiting time analysis using queuing theory methodologies into CSLP. For instance, Yi et al. (2019) formulated a mathematical model to optimize the location and capacity of charging stations, considering charging time, cost, and convenience as key indicators of driver satisfaction. Then, an $M/M/c$ queueing model was applied to calculate the waiting and service time during the charging process. To incorporate user preferences, Zhu et al. (2018) introduced a comprehensive model that considers users' costs, including access costs, charging costs, and the establishment costs of charging stations. This approach enhances the realism of the model by integrating various cost factors. The resulting model treats each charging station as an independent charging system and applies the $M/M/c$ queuing model to determine optimal locations and capacities for the charging stations. Likewise, Tian et al. (2018) proposed an optimization model based on queuing theory to minimize the cost of constructing EV charging stations and reducing the charging time. The model began by predicting the charging behaviors of drivers and subsequently employed an $M/M/c$ queuing model to determine the average waiting time for each charging station, treating them as individual queuing systems.

In an effort to model driver's reaction to long waiting times, Xiao et al. (2020) proposed a model to ascertain the best locations and capacity of EV charging stations to minimize the total cost. The model assumes a finite queue length by modelling each station as an $M/M/s_j/N$ model where s_j represents the number of chargers installed at charging stations j, and N is the maximum tolerable length of line. In all these studies, standard assumptions of queuing systems (e.g., Poisson arrivals, Exponential service durations, and first-come-first-served queue discipline) were used. Vijay et al. (2024) developed a two-stage optimal planning model for EVs to locate rapid charging stations. The model considers installation cost and waiting time at rapid charging stations. The waiting time is determined by $M/M/c$ queueing model. Wu et al. (2024) also developed a robust model to deal with uncertainty in charging demand. The model minimizes costs, including the monetary value of driving time to charging station, using $M/G/m/m$ queueing model. The model uses a linear approximation of loss rate (i.e., drivers leaving a station because it's full).

It should be noted that in real world situations, charging infrastructure networks expand over long-time horizons due to high capital costs of establishment and budgetary limitations. To study the expansion of charging infrastructure over an extended period of time, numerous studied were carried out in the literature (such as Xie et al., 2018, Li et al., 2016, and Perera et al., 2020) that offered a multi-period structure to study the evolution and expansion of charging stations network on a longer time basis in relation to the realized demand.

In addition, CSLP requires strategic decision making for which many input parameters (e.g., demand, costs, range, supply) are uncertain and could vary over time, spurring a recent interest towards stochastic CSLP (SCSLP) models. For instance, Kchaou-Boujelben and Gicquel (2020) have studied uncertain driving range of EVs. In the case of demand uncertainty, several methods are developed including predicting future demand (Hu et al., 2020), developing a two-stage stochastic model (Wu and Sioshansi, 2017), and employing a robust optimization model (Zhang et al., 2019).

To address range anxiety arising from inadequate charging infrastructure, various solutions have been explored in the literature. Guo et al. (2018) and Xu et al. (2020) advocated for optimal charging station locations, while Mak et al. (2012) investigated the deployment of battery-switching stations. Additionally, Zhang et al. (2021) proposed the development of fast charging stations.

Tzamakos et al. (2022) investigated the deployment of battery electric buses for urban transport and presented a model for equipping an electric bus network with fast wireless chargers. The model considers the expected delays of buses through an $M/M/1$ queuing model, and minimizes the investment costs. The model proposed by the authors introduced a maximum acceptable waiting time at terminal stops, which encompassed the anticipated waiting time in the queue and the charging duration. Wang et al. (2023) proposed a multi-stage optimization strategy for charging station locations for electric robotaxis.

Bai et al. (2019) proposed a model to determine the best location for EV charging stations, capacity options, and service types. They developed a hybrid NSGA-II with linear programming and neighborhood search to solve the problem and tested it using computer simulations. They also used the algorithm to design a charging station network in Shenzhen, China. Cintrano et al. (2021) introduced a multi-objective problem of locating electric vehicle charging stations in Málaga, balancing conflicting objectives of maximizing service quality and minimizing deployment costs. The proposed approach utilizes the NSGA to address the problem. The proposed approach is then compared with a deterministic exhaustive search method. Results indicate that the NSGA-based approach computes the most competitive solutions, showcasing diverse trade-offs between service quality and installation costs.

Cintrano and Toutouh (2022) proposed a multi-objective CSLP by maximizing charging station network service quality and minimizing deployment costs. The solutions involve two multi-objective metaheuristics: NSGA-II and Strength Pareto Evolutionary Algorithm 2 (SPEA2). The results showed that SPEA2 provides competitive solutions, while both NSGA-II and SPEA2 offer accurate sets of solutions with different trade-offs between service quality and installation costs. Zhang et al. (2023) addressed the CSLP, incorporating user preferences and waiting time using a multi-objective bi-level programming model. The proposed approach utilizes a Hybrid HNSGA-II with an embedded Level Determination Algorithm and a Partial Enumeration Algorithm. The sensitivity analysis provides insights into the EV charging station location practices.

Kumar et al. (2022) introduced a two-stage sustainable framework for the optimal allocation of fast charging stations, solar photovoltaic (PV), and battery energy storage systems (BESSs) with dynamic charging and discharging in a coupled distribution and transportation network. The first stage employs modified queueing theory and NSGA-II with fuzzy satisfaction-based hybrid optimization to model stochastic EV charging demand and optimize the location and sizing of PV-integrated EVCS. The second stage calculates the size of BESS and additional PV capacity for BESS charging using the bi-section method. Their proposed framework is validated on a bus distribution system coupled with a 25-node transportation network and demonstrated benefits such as reduced power losses and voltage deviation due to increased EV charging demand.

Wang et al. (2022) formulated a model for optimizing the location and capacity of charging stations, aiming to maximize operator revenue and minimize users' charging costs. Their model introduced a road time-consuming index to quantify the impact of road congestion on user costs, enhancing user satisfaction during charging. To address the planning model, a NSGA-II was proposed, utilizing chaos initialization and an arithmetic crossover operator. Simulating the Haidian District of Beijing, the results demonstrated an 11.4 % reduction in user lost time costs compared to scenarios where urban traffic networks were not considered. Ferraz et al. (2023) optimized electric vehicle charging station allocation and sizing to improve power quality and reduce installation and recharging costs. The objective functions encompassed considerations for the power quality indices and the reduction of costs associated with CS installation and EV users' recharging. Utilizing the NSGA-II for the IEEE 34-node test feeder, the approach leads to an 11.57 % reduction in voltage deviation, a 56.68 % decrease in power losses, and a minimal 4.44 % variation in energy costs, even with integrated EV loads.

Zapotecas-Martínez et al. (2024) applied NSGA-II and MOEA/D-gen algorithms to a real-life scenario involving charging station optimization for electric vehicles in an urban setting. Results showed a trade-off between travel time and the number of stations. The paper also shows that NSGA-II outperforms MOEA/D-gen, indicating its efficiency in finding optimal solutions. Their research sets the stage for exploring additional scenarios and *meta*-heuristics for the electric vehicle charging stations problem.

Recently, Industry 4.0 and its disruptive forces, as elaborated in Choi et al. (2022), provide an opportunity to further improve the operational and logistical efficiency of EVs and strengthening their position in transitioning to a more sustainable economy (Ahmed et al., 2021). For instance, internet of things (IoT) can be used to better forecast the demand for charging which can lead to better scheduling of charging operations and reduction of waiting times in stations Savari et al. (2020). Digital twin systems, as discussed in Liu et al. (2020) and Wang et al. (2020), can be used to enhance the safety of drivers, passengers, and pedestrians through development of advanced driver assistance systems (ADAS). Finally, artificial intelligence (AI) tools have been used to find trends and relationships between large data sets, or to enhance computational efficiency of solving complex optimization problems. For instance, reinforcement learning (RL) is widely applied to predict customers' demand and energy consumption during the routing of electric commercial vehicles (Basso et al., 2022), while an approach based on neural networks (NN) was developed in Ojo et al. (2020) to assist in thermal fault detection of electric batteries and to increase the overall safety of EVs. To summarize, Industry 4.0 technologies enhance the efficiency and effectiveness of logistics operations and transportation systems; however, these technologies also create huge challenges for modeling and optimization using traditional methods (Chung, 2021). Therefore, new research is required to address such challenges in the modeling and optimization of transportation systems.

Based on the reviewed literature, the following research gaps are listed:

- Prior studies presumed known probability distributions for arrivals and service processes (typically Poisson and Exponential, respectively). However, in real-world scenarios, these assumptions can be inaccurate, leading to flawed waiting time estimations and suboptimal investment decisions. For example, in EV charging stations, EV arrival rates can be influenced by factors like traffic, weather, time of day, and driver behavior, resulting in non-Poisson arrivals. Similarly, service durations at charging stations can vary due to factors like charging rate, EV state of charge, and weather conditions, which may not fit an Exponential distribution accurately.
- Prior SCSLP studies primarily concentrated on a single goal, like minimizing costs or maximizing service coverage. Nevertheless, real-world situations often demand balancing multiple competing objectives, such as minimizing wait times while keeping costs in check. In the SCSLP context, the scarcity of research exploring these trade-offs results in one-sided decisions that overlook various possibilities.

- In previous studies, the first-come-first-served (FCFS) strategy has been widely used for serving EVs in charging stations. While the FCFS strategy is practical and easy to implement, it may not always be the most efficient one. As such, it is important to investigate the efficiency of alternative strategies that works best in a given context.
- NSGA-II has been applied in multiple CSLP studies. It is due to its ability to handle bi-objective models and its superior performance over other algorithms, as presented in the literature. In addition, NSGA-II has been innovatively adjusted and expanded to deal with different problems; however, the literature review shows a lack of embarking machine learning methods in the algorithm to enhance its performance.
- AI-driven tools have gained traction in enhancing various EV operational aspects. In the context of SCSLP, existing queuing theory models struggle to accurately estimate waiting times for complex scenarios, potentially leading to suboptimal choices. Leveraging advanced AI techniques can offer more precise estimations, thereby enhancing strategic infrastructure decisions to support EVs. Improving EV operational efficiency by reducing waiting times is crucial for EV planners. To the best of our knowledge, this paper's contribution in developing and applying DNN is unmatched in the literature, providing valuable insights to accelerate EV mass adoption.

In summary, the above research gaps have important practical implications for various stakeholders. The proposed framework in this paper aims to bridge these gaps to help improve strategic decision-making in this context, thereby eventually accelerate the widespread popularity and adoption of EVs.

3. Problem description

Using a set of nodes, N, and a set of edges, E, the mobility network for EVs can be presented as a $G = (N, E)$. Every node $n \in N$ is considered an origin, destination, or candidate location for charging stations. Set K (indexed by $k \in K$), therefore, represents all the candidate nodes for hosting charging stations. EVs are travelling from their origins to their destinations through the optimal path in the network (e.g., shortest path) during the day, and demands are defined for Origin-Destination pairs. Each demand w is a six-tuple ($i_w, j_w, l_w, f_w, k_w, m_w$) where $i_u \in N$is the origin node for demand w, $j_u \in N$ is the destination node for demand w, l_u is the initial charging level of EVs for demand w, f_w is the flow of EVs corresponding to demand w, k_w is the set of nodes in which demand w should stop to get recharged to reach its destination, and m_w is set of ordered pairs of (node, charging level) that demand w can reach. Each charging station consists of a set of charging piles. Because the average waiting time is a measure of charging station overall performance, the number of charging piles is considered as a critical decision in this problem. The entrance of EVs to charging stations is considered a stochastic process in which a general probability distribution is used to represent the arrival rates of EVs to the charging stations. There are L different lines in each station and each line is equipped with C parallel identical piles. EVs are allocated to the lines according to their charging level such that EVs which need less charging time have the chance to avoid waiting behind EVs that need more charging time. This strategy leads to reducing the average waiting time.

Each demand w must be charged at a subset of possible charging stations denoted by k_w. The way demands are assigned to the charging stations highly affects the congestion in charging stations. Therefore, the configuration decisions include the optimal number of charging piles per each line of charging station. To this aim, a bi-objective mathematical model is developed to minimize 1) the total cost of constructing charging stations (as the first objective function) and 2) the average waiting time of all EVs in the network that are served in the charging stations (as the second objective function). The charging process itself is modelled as a $GI/GI/c$ queueing system. By considering general probability distributions and integrating a queueing theory model with a mathematical programming model, the proposed framework provides a comprehensive analysis of the charging process across the network.

The next section will elaborate on the model assumptions and the related notation in this paper.

3.1. Assumptions

The following assumptions are considered for the model formulation:

- A charging pile can only serve one EV at a time.
- The availability of land and electrical load imposes constraints on the number of charging piles that can be installed in each charging station.
- EVs are discharged at the same rate.
- Parameter f_w, that represents the flow of EVs between each pair of Origin-Destination (demand), is explicitly defined as a probabilistic parameter that follows a general probability distribution with a known mean, denoted by $\lambda_{i,j,l}^{O-D}$, and squared coefficient of variation, denoted by $\delta_{i,j,l}^{O-D}$(please see notations).
- The edge lengths of the network are limited by the maximum distance EVs can travel with their initial charge.
- Each EV needs to be charged at most once before reaching its destination. This assumption is grounded in the expectation that only a small number of EVs would need to recharge more than once daily for their regular commuting purposes (Wu and Sioshansi, 2017). For example, the average American driver drives 60 km per day (Jankord, 2020). Moreover, the average daily driving distance in Europe is 43 km per day (Vialetto et al., 2017). Given that most EVs have a range of 200–400 km per charge, only a negligible portion of EVs would necessitate multiple charging stops.

- The assumption of varying fixed construction costs for potential locations is commonly made in the literature (Xiao et al., 2020). Similarly, the costs associated with purchasing and installing a charging pile unit differ among candidate locations, reflecting variations in construction and labor costs across different regions (Nie and Ghamami, 2013). EVs are assigned to a line in each charging station based on their charging level upon arrival.
- The proposed model suggests the location decision based on the optimization model; however, the ultimate decision regarding the location of charging station is made by an EV driver.

3.2. Model notations

To formulate the proposed model, the sets, parameters, and decision variables are explained in this section. Each demand w is characterized by a six-tuple $(i_w, j_w, l_w, f_w, k_w, m_w)$ in which i_w and j_w show the origin and destination nodes that belong to the set N. k_w denotes the set of nodes wherein demand w with origin and destination of i_w and j_w and the initial charging level of l_w should be recharged. For every demand w, the values of k_w are used to create the set $N_{i,j,l}$. To gain a more comprehensive understanding of the calculation of $N_{i,j,l}$, it is helpful to consider an example as depicted in Fig. 1. The coloured line represents the charging status spectrum, with green showing a fully charged battery. As the line gradually turns red, it indicates the depletion of the charge, and the red segment indicates the point at which the charge is fully exhausted. The route includes a series of nodes, from 1 to 11. Let's assume the distance between two consecutive nodes is 20 km. In this example, demand (EV) has a total of 6 charging levels, and the range of 120 km travels from an origin node ($i_w = 1$) to a destination node ($j_w = 10$). It has an initial charging level of 4 which indicates a range between 60 and 80 km. With the initial charging level, the demand can go at most 80 km which means it can reach node 5 and cannot complete its intended journey. If EV is charged at its origin, it will extend its range to 120 km and can reach node 7; however, it still falls short of the intended destination. Similarly, using charging plans of 2 or 3, involving charging at nodes 2 or 3, respectively, does not let the demand reach its destination. In fact, charging in either node 4 or 5 is the only charging plan that would allow demand w reaching its destination (node 10). Therefore, set $N_{1,10,3}$ consists of charging plans 4 and 5 and thus $N_{1,10,3} = \{4,5\}$. The demands whose set $N_{i,j,l}$ becomes empty imply that the initial charging level is sufficient to reach to their destination. This approach let us release the assumption that all EVs need to be charged in their route.

If a demand reaches node k with charging level m it may have originated from a set of nodes with a specific initial charging level. This set is defined by set $M_{k,m}$. For example, $M_{5,2} = \{(1, 8), (2,6), (4, 3)\}$ implies that a demand that starts at node 1 with charging level 8, or starts at node 2 with charging level 6, or starts at node 4 with charging level 3, all will have charging level 2 when they reach node 5.

Sets and indexes	
K	Set of candidate nodes for establishing charging stations denoted by k
N	Set of origin and destination nodes $N \subseteq K$ indexed by i and j
$N_{i,j,l}$	Set of nodes that EVs with origin i, destination j, and initial charging level l should stop before getting to their destination
$M_{k,m}$	Set of ordered pairs of origin node (i) and charging level (l). Each member of the set shows a possible origin and initial charging level for EV that is currently at node k and has charging level m
L	Set of charging levels indexed by l and m
Parameters	
f_k^1	Fixed cost of constructing a station in each candidate location k
f_k^2	Fixed cost of installing a pile in each charging station k
$\lambda_{i,j,l}^{O-D}$	Average arrival rate of EVs with origin i, destination j, and initial charging level l
$\delta_{i,j,l}^{O-D}$	Squared coefficient of variation of the arrival rate of EVs with origin i, destination j, and initial charging level l
$\mu_{k,m}$	Average charging time of EVs at charging station k with charging level m
$\eta_{k,m}$	Squared coefficient of variation of charging time of EVs at charging station k with charging level m
Max_k	Upper bound of the number of piles in each charging station k
M	A large positive number
Auxiliary variables	
$\lambda_{k,m}$	EVs average arrival rate to charging station k with charging level m
$\zeta_{k,m}$	Squared coefficient of variation of EVs arrival rate to charging station k with charging level m
$WT_{k,m}(GI/GI/C_{k,m})$	Average waiting time of EVs that reach charging station k with charging level m
Decision variables	
Y_k	$\begin{cases} 1 ifachargingstationisconstructedatnodek \\ 0 Otherwise \end{cases}$
$X_{i,j,l,k}$	$\begin{cases} 1 ifEVswithorigini, destinationj, andcharginglevellstopatnodektobecharged \\ 0 Otherwise \end{cases}$
$C_{k,m}$	The number of piles at charging station k assigned to EVs with charging level m

3.3. Objective functions

The model seeks to optimize two objectives together. The first objective minimizes the overall costs associated with setting up charging stations:

$$MinZ_1 = \sum_{\forall k} f_k^1 Y_k + \sum_{\forall k}\sum_{\forall m} f_k^2 C_{k,m} Y_k \tag{1}$$

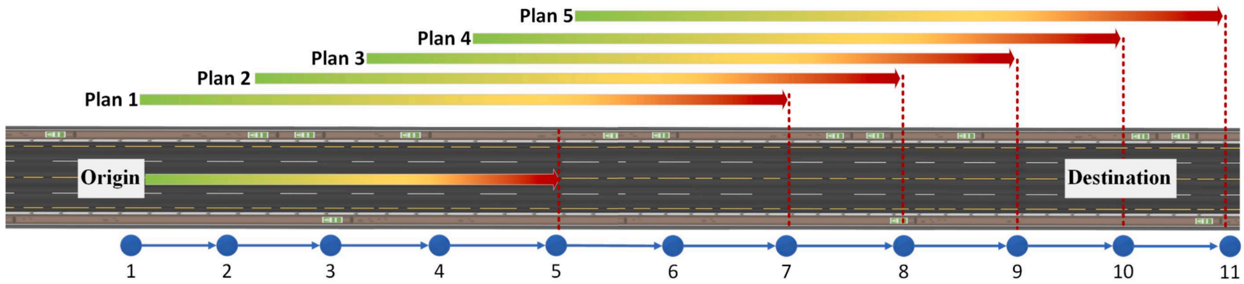

Fig. 1. An example of charging plan analysis for the calculation of $N_{i,j,l}$ (The length of the colored line represents the range, and the dark green section of the line indicates a complete charge, while the vertical dotted red lines show where the charge is fully exhausted). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Also, the model aims to minimize the total average waiting time of EVs in the charging stations across the network. To this aim, queueing theory formulations are used. Fig. 2 illustrates the queue mapping approach for a charging station located at node k. There are L distinct lines in this charging station, where lines 1, 2 and L consists of 4, 2 and 3 identical piles in parallel, respectively. Therefore, multi-server queueing system enable us to model each line of the charging stations.

To offer a more realistic perspective, a situation in which EVs inter-arrival and charging rates are probabilistic parameters with general probability distributions is considered. As a result, the model is not limited to some predefined Poisson, Exponential, or other probability distributions. Consequently, the behaviour of lines in each charging station is modelled as a generally distributed queueing system ($GI/GI/c$).

The arrival process and charging process are described using the fundamentals of two-moment approximations which are frequently used in the literature on queueing systems to estimate performance measures such as the average waiting time (Shortle et al., 2018; Medhi, 2002), as shown in this section. Let $P_{0,k,m}$ represent the probability that charging station k has no EVs with charging level m, and $\rho_{k,m}$ be the service density of piles in line m of station k. Then,

$$P_{0,k,m} = \left[\sum_{m=0}^{C_{k,m}-1} \frac{(C_{k,m}\rho_{k,m})^m}{m!} + \frac{(C_{k,m}\rho_{k,m})^{C_{k,m}}}{C_{k,m}!(1-\rho_{k,m})} \right]^{-1} \forall k, \forall m \tag{2}$$

Fig. 2. Queueing system in charging stations.

$$\rho_{k,m} = \frac{\lambda_{k,m}}{C_{k,m} \times \mu_{k,m}}, \forall k, \forall m \tag{3}$$

Also, let $WT_{k,m}(M/M/C_{k,m})$ be the average waiting time for an $M/M/C_{k,m}$ queueing system calculated as Eq. (4) (Ross, 2014):

$$WT_{k,m}\left(\frac{\frac{M}{M}}{C_{k,m}}\right) = \frac{P_{0,k,m}\left(\frac{\lambda_{k,m}}{\mu_{k,m}}\right)^{C_{k,m}}\rho_{k,m}}{C_{k,m}!\left(1-\rho_{k,m}\right)^2\lambda_{k,m}}, \forall k, \forall m \tag{4}$$

Then, the average waiting time for $GI/GI/C_{k,m}$ queueing model is:

$$WT_{k,m}(GI/GI/C_{k,m}) \approx \left(\frac{\zeta_{k,m} + \eta_{k,m}}{2}\right) WT_{k,m}(M/M/C_{k,m}) \forall k, \forall m \tag{5}$$

By assuming $\rho_{k,m} < 1$, which implies that the arrival rate of EVs is less than the multiplication of the service rate and the number of piles, the queueing system will be stable. Finally, the second objective function is formulated as Eq. (6) which reduces the total average waiting time of EVs in charging stations.

$$MinZ_2 = \sum_{\forall k}\sum_{\forall m} WT_{k,m}(GI/GI/C_{k,m}) \tag{6}$$

3.4. Constraints

This section elaborates on the constraints used to formulate the problem.

3.4.1. EV charging requirements

EVs should reach their destinations without running out of battery, and thus, their batteries should be recharged at one of the charging stations belonging to set $N_{i,j,l}$. This requirement is satisfied by constraint set (7). Constraint set (8) makes sure that EVs are allocated to the charging stations that have been already constructed.

$$\sum_{\forall k \in N_{i,j,l}} X_{i,j,l,k} = 1, \forall i, \forall j, \forall l \tag{7}$$

$$\sum_{\forall i}\sum_{\forall j}\sum_{\forall l} X_{i,j,l,k} \le MY_k, \forall k \tag{8}$$

3.4.2. Arrival rate constraints

The average and SCV of arrival rate of EVs with charging level m to each charging station k are calculated using Eqs. (9)-(10). Eq. (9) calculates the average arrival rate of EVs with a specific charging level m at each charging station k. To do this, the summation of average arrival rates over all origin nodes i and charging levels l is calculation if they are a part of the set $M_{k,m}$. Also, for each origin, the summation of average arrival rate over all possible destination nodes j is computed. $M_{k,m}$ represents the set of nodes and charging levels that result in an EV reaching charging station k with charging level m. Eq. (10) extends the analysis by focusing on SCV of the arrival rate of EVs with charging level m at each charging station k. Similar to Eq. (9), it considers all possible origins i and charging levels l in the set $M_{k,m}$. The term $\delta_{i,j,l}^{O-D}$ represents the SCV of the arrival rate associated with the journey from origin i to destination j with initial charging level l. In fact, this equation captures how each value of $\delta_{i,j,l}^{O-D}$ can contribute to the final value of SCV of the arrival rate of EVs with charging level m at charging station k.

$$\sum_{\forall j}\sum_{\forall (i,l) \in M_{k,m}} \lambda_{i,j,l}^{O-D} X_{i,j,l,k} \le \lambda_{k,m}, \forall k, \forall m \tag{9}$$

$$\sum_{\forall j}\sum_{\forall (i,l) \in M_{k,m}} \frac{\lambda_{i,j,l}^{O-D} X_{i,j,l,k}}{\lambda_{k,m}} \delta_{i,j,l}^{O-D} \le \zeta_{k,m}, \forall k, \forall m \tag{10}$$

3.4.3. Quantity of charging piles

To mitigate capacity constraints in the electricity supply network, a maximum limit should be imposed on the number of piles to be installed at each station. This limitation is ensured by constraint set (11).

$$\sum_{\forall m} C_{k,m} \le Max_k \quad \forall k \tag{11}$$

3.4.4. Domain

The decision variables are bounded by constraint sets (12) and (13).

$$X_{i,j,l,k}, Y_k \in \{0, 1\}, \forall i, j, l, k \tag{12}$$

$$C_{k,m} \in \{0, 1, 2, \cdots, L\}, \forall k, m \tag{13}$$

4. Proposed solution approach

The proposed model initially applied queueing theory formulations to estimate waiting times at charging stations. However, it's crucial to note that when dealing with $GI/GI/c$ queueing systems, the use of such formulations can introduce substantial errors, ranging from 1 % to as high as 15 %. In worst-case scenarios, these errors can reach a staggering 31 % (Chaves and Gosavi, 2022; Medhi, 2002). The importance of accurate waiting time estimations in transportation cannot be overstated. Even a minor deviation from the actual waiting time can lead to significant costs and passenger dissatisfaction. Hence, it is imperative to minimize the margin of error introduced by queueing approximations.

To overcome this limitation, this paper introduces an innovative approach that seamlessly integrates machine learning algorithms with queueing theory to significantly enhance the precision of waiting time estimation. The proposed methodology commences by constructing a comprehensive simulation model of the charging station network, subjecting it to a diverse array of scenarios. This simulation model serves as a crucial component of the proposed approach. It enables the creation of data that closely mimics real-world scenarios, offering an excellent training environment for machine learning algorithms.

The next step in the proposed method is creating a computer simulation that acts like a virtual charging station. The simulation is run for different scenarios. Each scenario corresponds to a line in a charging station with specific features such as average and SCV of arrival and service rates, and number of charging piles. Moreover, the waiting time for each scenario is estimated by the queueing theory formula and is used as another input feature of the scenario. As the final step, all the features and the estimated waiting times by simulation model are used to train a DNN. Upon completion of the training process, DNN demonstrates high precision in estimating the waiting time, which is employed as a part of the second objective function in the model. It should be added that the proposed mathematical model is non-convex and falls under the MINLP category, and thus, standard commercial solvers can only optimize the modes for small-scale instances. Given the structure of the model, the model is optimized using a bi-objective *meta*-heuristic algorithm. To this end, the NSGA-II algorithm which has shown promising performance in addressing similar multi-objective problems has been used in this paper (Zhang et al., 2023; Farahani et al., 2010). In the improved NSGA-II, a heuristic selection operator is applied which leads to better results compared to normal NSGA-II. The details of the DNN and NSGA-II are depicted in Fig. 3 and are elaborated as follows.

4.1. Deep learning algorithm

Machine learning (ML) algorithms achieve optimal estimation of output for unseen inputs (Damirchilo et al., 2021; Kotsiopoulos

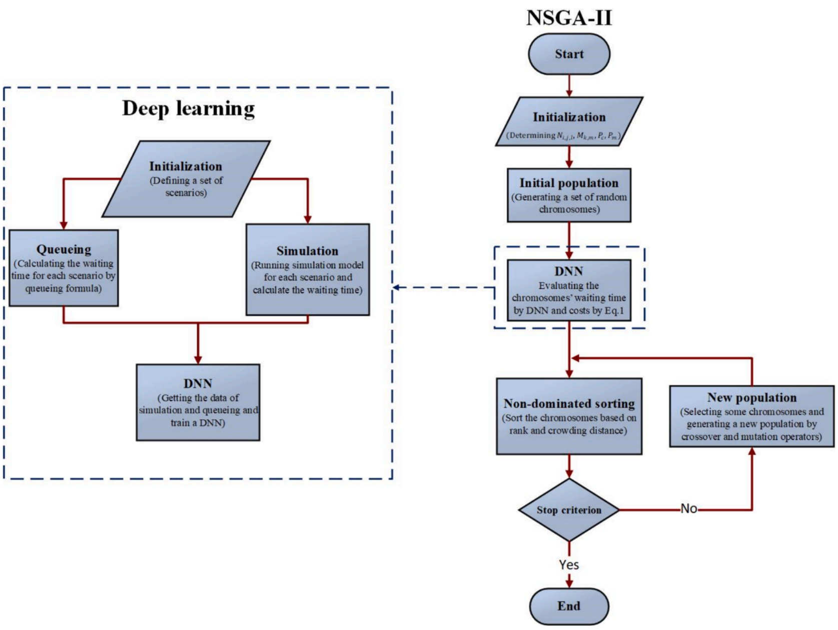

Fig. 3. Flow chart illustrating steps of the proposed approach.

et al., 2021). Among several ML algorithms used, this article applies a deep neural network (DNN) model. A DNN is an artificial neural network (ANN) with additional hidden layers between the input and output layers (Yuvaraj et al., 2020). DNNs are inspired by the examination of bio-electrical networks in the brain and consist of interconnected neurons with weighted connections. Each neuron computes its output value based on a weighted sum of its inputs and an activation function. The learning process involves modifying the weights between neurons in the neural network to enhance the prediction capability of the DNN (Nielsen, 2015). The increased depth enables DNNs to achieve a higher performance in learning and approximating complex relationships between inputs and outputs (Kang et al., 2020; Zheng et al., 2021).

In the proposed approach, a DNN is trained and used to estimate the waiting times of EVs in the charging stations network. The DNN used in this study is a fully connected feed-forward neural network that benefits from the backpropagation algorithm to train the network. The DNN involves six layers in total (i.e., single input layer, four hidden layers, and single output layer). The input layer receives inputs from the external environment using neurons. In this problem, as presented in Fig. 3, the inputs are the average and SCV of arrival rates, the average and SCV of charging rates, the number of piles, and the waiting time estimated by queueing theory. The output layer represents the response variable which is the average waiting times of EVs. The hidden layers act as a black box to find the relationship between inputs and output. The appropriate number of neurons in the hidden layer is often decided through experimentation and trial and error (Tsai and Hung, 2016). For this study, the first, second, third, and fourth hidden layer contains 100, 120, 120, and 120 neurons respectively with activation function ReLU defined as follows:

$$\varphi(x) = Max(0, x) \tag{14}$$

A linear activation function is used for the output neuron to return the weighted sum of the inputs directly. In Fig. 4, $\varphi_{1,j}$ is the output of each neuron j of hidden layer 1 which is calculated by Eq. (15).

$$\varphi_{1,j} = Max\left(0, \sum_{i=1}^{6} \left(w_{i,j}X_i\right) + b_{1,j}\right) \tag{15}$$

where W_{ij} is the weight connecting the i^{th} decision variable to the j^{th} neuron, 6 is the number of input variables and $b_{1,j}$ is the bias of the j^{th} neuron. The inclusion of a bias value is crucial in shifting the activation function, enabling successful learning. For hidden layers 2, 3, and 4 Eq. (16) is used to calculate the output of each neuron:

$$\varphi_{k,j} = Max\left(0, \sum_{i=1}^{ne_{k-1}} \left(w_{k-1,i,j}\varphi_{k-1,i}\right) + b_{k,j}\right) \tag{16}$$

where $\varphi_{k,j}$ is the output of the j^{th} neuron of the k^{th} hidden layer, $w_{k-1,i,j}$ for the weight connecting the i^{th} neuron of layer k-1 to the j^{th} neuron of layer k, $b_{k,j}$ is the bias of the j^{th} neuron of layer k and ne_{k-1} is the number of neurons in layer $k-1$. For the output layer, a linear function is generated by layer weights and the bias b' to estimate the response variable (waiting time):

$$Y = \sum_{i=1}^{120} \left(w_{4,i}\varphi_{4,i}\right) + b' \tag{17}$$

4.2. Non-dominated sorting genetic algorithm (NSGA-II) optimization

NSGA-II is a powerful algorithm widely used to solve multi-objective optimization problems in CSLPs (Bai et al., 2019; Cintrano and Toutouh, 2022; Zhang et al., 2023; and Kumar et al., 2022; Zapotecas-Martínez et al., 2024). NSGA-II utilizes a randomized approach to generate a parent population of potential solutions. The population is then divided into multiple fronts of non-dominated chromosomes (solution), with each chromosome assigned a rank based on its respective front. Following this, a metric, named crowding distance, is calculated for each chromosome. The rank and crowding distance information are used to select chromosomes through a binary tournament selection operator for the crossover and mutation operators, generating a new population for the next iteration. Ultimately, a set of non-dominated Pareto-optimal solutions are obtained (Deb et al., 2002). Detailed steps of NSGA-II are available in Deb et al., (2002). The next subsections explain the essential characteristics of NSGA-II in the context of this problem formulation, which are chromosome representation, crossover and mutation operators, and how to preserve the feasibility.

4.2.1. Chromosome representation

The process of encoding a solution as a chromosome is a critical step in implementing NSGA-II. Fig. 5 illustrates that a chromosome is comprised of two distinct parts. The first part represents the allocation pattern of demands to charging stations, denoted as variable $X_{i,j,l,k}$, and the second part is related to the number of piles installed in each station, denoted by variable $C_{k,m}$. For the first part, a three-dimensional matrix $MX_{|i||j||l|}$ is used in which the value of cell (i,j,l) indicates the selected charging stations for demand with Origin-Destination pair of (i,j) and initial charging level l. NA means that there is no demand between a given Origin-Destination pair. For instance, consider an example in which EVs with Origin of 1 and Destination of 6 and an initial charging level 2, have candidate locations of nodes 2, 3, and 4, denoted by $N_{1,6,2} = \{2,3,4\}$. In this case, the value of $MX_{1,6,2} = 3$ indicates that the charging station at node 3 is selected for EVs with an Origin of 1 and Destination of 6 and initial charging level 2. This representation ensures that all demands are addressed through their associated charging station, thereby guaranteeing the feasibility of the chromosomes. The second

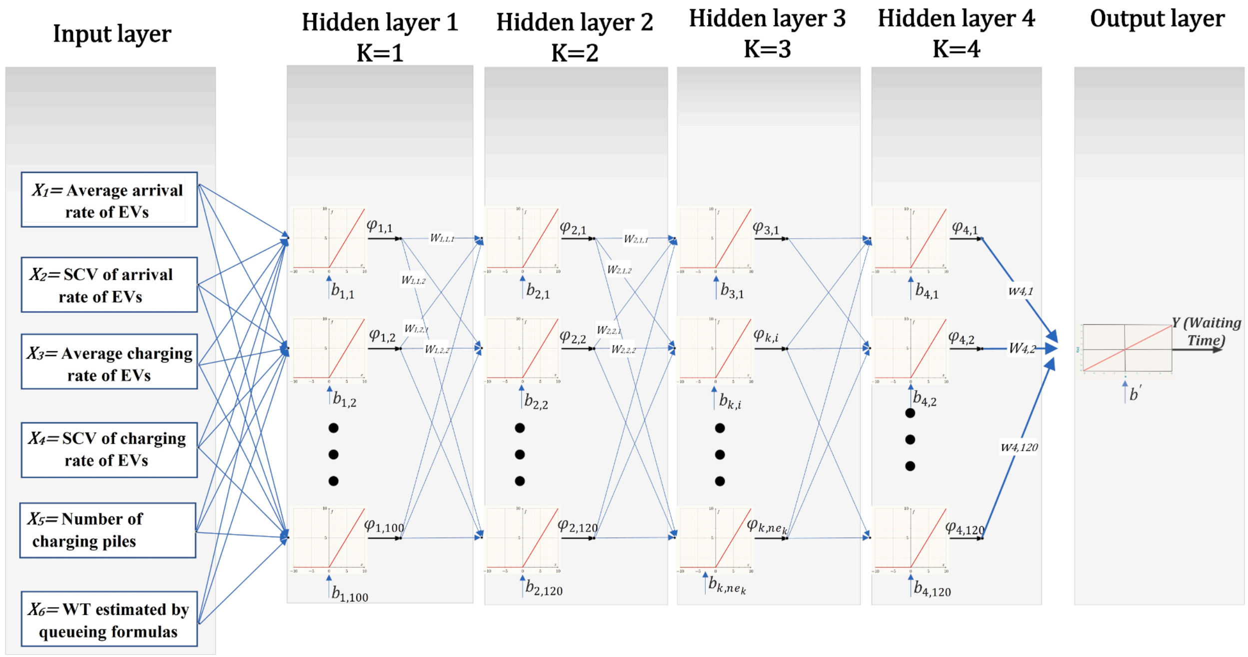

Fig. 4. The representation of the proposed DNN structure.

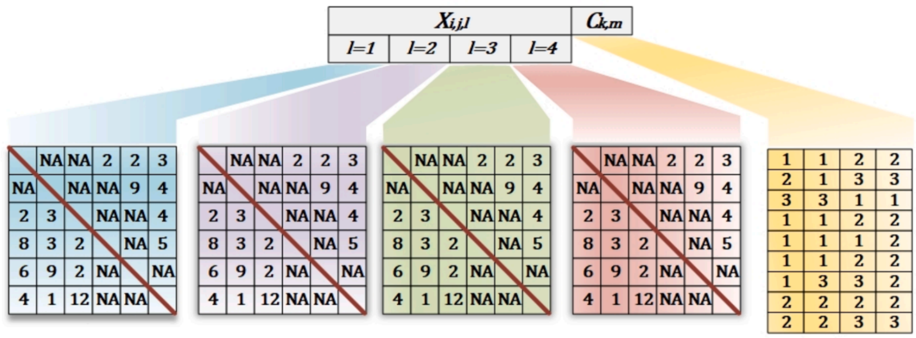

Fig. 5. Chromosome representation.

part of the chromosome is a $MX_{|k||m|}$ matrix where $|k|$ is the quantity of constructed stations, and $|m|$ is the number of lines in charging stations. TEach cell (k, m) represents the quantity of piles in line m of charging station k. Each row k is populated with m random numbers to satisfy the condition of their sum being less than or equal to the maximum allowable number of piles, denoted as Max_k. As a result, the constraints related to the maximum pile count are satisfied.

4.2.2. Genetic operators

NSGA-II algorithm utilizes various genetic operators, including selection, crossover, and mutation, to create fresh solutions. The algorithm employs pattern-based crossover during the process, whereby two parent solutions are combined to produce two distinct offspring solutions. The process of applying crossover to the first segment of the chromosome involves generating a random binary matrix, referred to as $rand_{|i||j||l|}$. A value of 1 denotes that the corresponding cell in the offspring should be identical to that of the first parent, whereas a value of 0 shows that it should be identical to that of the second parent. The second offspring is produced using the inverse order. In the case of the mutation operator, the matrix related to the second part of the chromosome is selected, and all rows are arranged in reverse order. Both the crossover and mutation operators ensure that the chromosomes remain feasible.

The selection operator is a pivotal component within NSGA-II algorithms, profoundly influencing optimization outcomes. In the standard NSGA-II, chromosomes are typically ranked and selected as parents based on their rank and crowding distance, favoring the better-performing individuals. However, the proposed heuristic selection approach introduces a departure from this norm. Here, each chromosome is chosen as a parent based on a probabilistic value obtained by training a neural network to calculate the likelihood of selecting each chromosome within the population. To train the neural network defining the features and label for each chromosome is required. The features of each chromosome are set as objective values, while the label, a value between zeros and one, indicates the likelihood of selection. Eqs. (18) and (19) are used to calculate the label of each chromosome.

$$a_i = \frac{f_{1i}}{\sum_{j=1}^{N} f_{1i}} + \frac{f_{2i}}{\sum_{j=1}^{N} f_{2i}} + \frac{rank_i}{\sum_{j=1}^{N} rank_i} - \frac{CD_i}{\sum_{j=1}^{N} CD_i} \tag{18}$$

$$p_i = \frac{\max_i a_i - a_i}{\sum_{i=1}^{N} a_i} \tag{19}$$

where f_{1i} and f_{2i} are the values of the first and second objective functions of chromosome i, while $rank_i$ and CD_i are the front number and crowding distance of chromosome i, N refers to the number of chromosomes in the population, and p_i is the likelihood of selecting the chromosome i. Eq. (18) calculates the summation of the normalized input features. Since the lower value of a_i should be given a higher likelihood of selection, Eq. (19) is used to a max–min normalization.

Once the neural network is trained, it is integrated into the NSGA-II algorithm as the selection operator. It replaces the traditional binary tournament selection with the probabilities predicted by the neural network. The major advantage of this integration lies in its ability to make parents selection process more intelligent and adaptive.

5. Computational results

This section presents computational experiments conducted to assess the performance of the proposed approach. The first subsection involves generating a network graph. The subsequent subsection entails training the DNN using a simulation model. NSGA-II is then executed to obtain a collection of optimal solutions. Finally, the sensitivity analysis is performed based on the variability of the input parameters. All computational experiments were implemented on 8 GB RAM computer using an Intel Core i7 CPU (2.3 GH) processor. The simulation model was implemented using Enterprise Dynamics® 10.5 software package. The NSGA-II and DNN were both implemented in Python 3.6 environment while the Keras library as a TensorFlow backend (Abadi et al., 2016) was used for the DNN.

5.1. Graph generation

In this section, a network topology is demonstrated to calculate the performance of the proposed approach. The area of interest spans 1,632 km^2, encompassing the metropolitan regions of Halifax (NS) and its environs. Fig. 6 depicts the network and its corresponding topology inclusive of Origin-Destination nodes. The network topology, which comprises nodes, edges, and communication protocols, is derived from Google Maps using the OSMNX library. This representation provides insight into the physical and logical structure of the network. There is a total of 177,556 nodes and 343,857 links within the network. It is assumed that the area is divided into numerous non-overlapping zones, with the centers of each zone serving as origin or destination nodes. These nodes are connected directly to the Origin-Destination nodes of adjacent zones via the shortest available paths. Taking advantage of OSMNX, the distance between each Origin-Destination pair is the shortest driving distance obtained according to Google Maps. The gravity model is used to measure the traffic flow of each Origin-Destination pair (Hodgson, 1990):

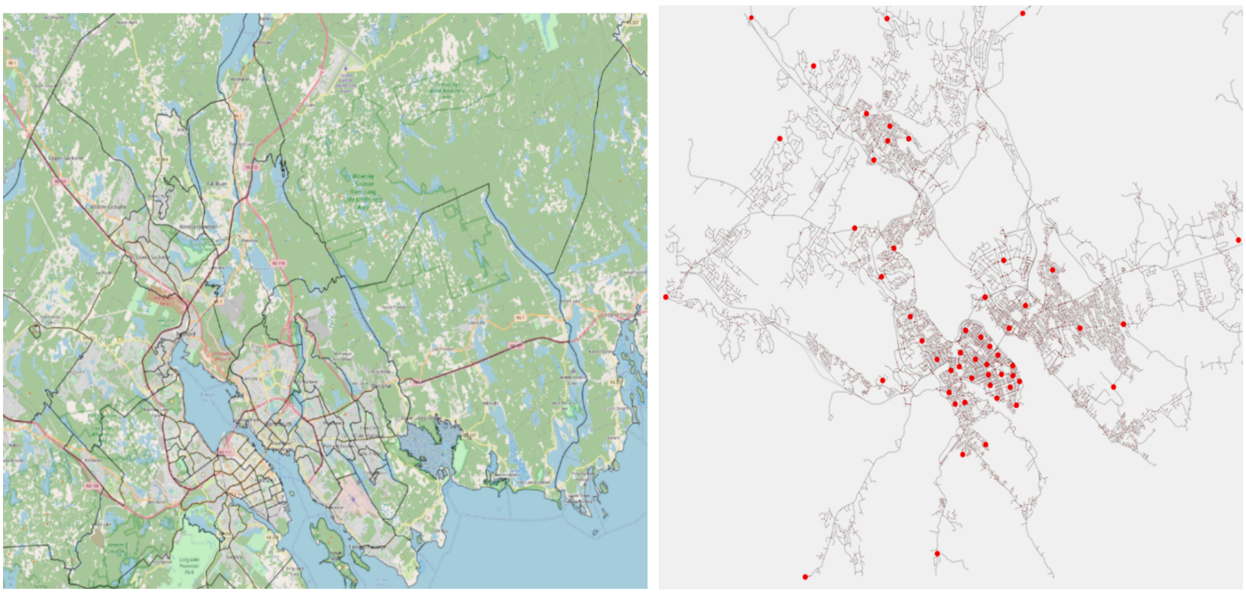

Fig. 6. Area of interest (left) and its topology (right).

$$\lambda_{i,j,l}^{O-D} = \beta \frac{w_i w_j}{D_{i,j}} \tag{20}$$

where $\lambda_{i,j,l}^{O-D}$ is the average traffic flow in a particular Origin-Destination pair in which the origin node is i and the destination node is j, with the shortest path distance $D_{i,j}$. Associated weights for nodes i and j, are shown by w_i and w_j, respectively. In the elastic demand function, the parameter $\beta = 0.01$. The data pertaining to the population and geographical position of each zone is available online.[1]

The network is streamlined by identifying the shortest paths between all Origin-Destination pairs. Nodes that lie along these paths are retained, while the remaining nodes are removed. Each origin or destination node is then considered as a candidate location for charging stations. Fig. 7 presents the final graph along with the origin or destination nodes and other candidate nodes to provide a clear visual representation.

The graph contains a maximum distance of 138.486 km between a given origin and a given destination node, which can be covered using 50 % of an electric vehicle's battery capacity. Consequently, EVs with an initial battery capacity of more than 50 % are not considered. To implement a line-based strategy, charging stations are divided into lines and EVs are allocated to charging lines based on their state of charge (SoC). More specifically, EVs are categorized into ten levels based on their SoC, with level 1 representing a battery charge of 1 % to 5 % and level 10 representing a charge of 45 % to 50 %. Within each line, EVs with similar Soc will then be lined up. This prioritization scheme differs significantly from FCFS approach, where EVs are prioritized solely based on their arrival time at the charging station, without considering their charging needs. The charging rate of EVs is determined by their SoC level. EVs with a low SoC level require more time to charge than those with a higher SoC level. A linear relationship between the charging rate and SoC level is assumed, such that the average charging rate ($\mu_{k,m}$) is set to a $2 \times$ *charginglevel*. Therefore, for an EV with SoC level 1, the parameters $\mu_{k,m}$ is set to 2, indicating that two EVs can be charged every hour. By increasing the SoC level, the charging time decreases, and the average charging rate increases. Table 1 presents additional data used in the model.

5.2. Training DNN

The DNN should be trained to predict the waiting times in charging stations' queues. To accomplish this, the following steps should be implemented:

1. According to the five factors that impact the waiting time, a set of data points is generated (see Table 2, columns 2–6). Each data point represents a special configuration of a charging station line. For instance, the data point one shows an average arrival rate and service rate of 13 and 4 per hour, respectively. The SCV of the arrival and service rates of EVs are 0.370 and 0.492, respectively, and there are four charging piles available.
2. A simulation model of charging stations is constructed and tailored to each data point. The model is subsequently run 30 times, and the average waiting times are recorded.
3. The average waiting time of each data point is calculated through the queueing theory formulations.
4. The dataset used to train the DNN comprises data points and their associated average waiting time. These waiting times were calculated using both a simulation model and a queueing theory formulation (see Table 2).

The dataset used to train the DNN model was divided into two subsets: the training set and the validation set. The subsets were divided in a ratio of 0.8 and 0.20, respectively. The training set is the larger subset and is used to train the model to learn from the data. It should be added that the k-fold cross-validation method (with $k = 5$ folds) was used for validating the results, where the training set includes four folds (80 % of the data), and the remaining fold (20 % of the data) was kept as the validation set. The training process was iterated five times, with a different portion of the data used for validation each time, while the remaining four folds were used for training. This allowed for evaluating the model's performance during training and optimizing its hyperparameters. This cross-validation approach ensures that the model was trained on a large and diverse training set, while also being validated and optimized on unobserved data.

The aim of DNN training is to minimize the disparity between the predicted and actual outputs by determining the optimal set of weights and biases. Appendix A shows the details of finding an appropriate optimizer for the DNN algorithm and Table 3 presents the findings of related experiments used to clarify the final specification of the DNN.

5.3. Analysing the Pareto optimal solutions

The NSGA-II algorithm was utilized to determine the optimal decisions based on the graph generated in section 5.1. To comprehensively evaluate the performance of the proposed approach, both the normal NSGA-II and the NSGA-II that was improved by the heuristic selection (i.e., improved NSGA-II) were executed. This study assessed various combinations of population size, number of generations, cross-over rate, and mutation rate to identify the optimal parameter setting for both normal NSGA-II and the improved NSGA-II. Table 4 displays the Pareto front solutions generated by both Normal NSGA-II and Improved NSGA-II, including the number of stations and piles, as well as their corresponding objective function values. For the results presented in Table 4, Fig. 8 provides a

[1] https://www.citypopulation.de/en/canada/metrohalifax/.

Fig. 7. The Final Graph of Network (red lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
The value of some input parameters.

f_k^1	\$900,000 (Xiao et al., 2020)
$f_{k,l}^2$	\$120,000 (Xiao et al., 2020)
$\lambda_{i,j,l}^{O-D}$	Eq. (20)
$\delta_{i,j,l}^{O-D}$	$U(0.1, 0.6)$
$\mu_{k,m}$	$2 \times charginglevel$
$\eta_{k,m}$	$U(0.1, 0.6)$
Max_k	$U(20, 30)$

Table 2
The dataset for training and validation of DNN.

Data No	x_1	x_2	x_3	x_4	x_5	WT(Queue formulation)	WT(simulation)
1	13	0.370	4	0.492	4	140	153
2	12	0.554	10	0.384	2	46	54
3	19	0.409	5	0.209	4	335	362
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
199	29	0.492	3	0.569	10	896	1042
200	10	0.421	3	0.686	4	386	411

Table 3
Hyperparameters of DNN.

Hyperparameter	Value
Number of hidden layers	4
Size of hidden layers	[100, 120, 120, 120]
Activation function	[ReLU, ReLU, ReLU, Linear]
Number of epochs	50
Batch size	10
Learning rate	0.001
Loss function	Mean squared error (MSE)
Optimizer	Adam

visual representation of the trade-offs between the cost and the average waiting time.

The solutions produced by the Improved NSGA-II algorithm represent a more favorable balance between cost and waiting time, making them the preferred choice for guiding subsequent planning and configuration decisions for EV charging stations. The Pareto fronts of both algorithms are compared using Mean Ideal Distance (MID) metric (please see Appendix B). As a result, the improved NSGA-II shows 12.77 % improvement in solutions compared to the standard NSGA-11. These results not only offer cost savings but also enhance user satisfaction and overall operational efficiency, aligning more closely with the goals of sustainable and efficient transportation networks. Since the Pareto front generated by the improved NSGA-II algorithm outperforms that of the normal NSGA-II, our focus will be directed towards the results obtained using the improved NSGA-II algorithm for further in-depth analysis and decision-making processes. The Pareto front consists of 8 solutions, with costs ranging from $5.52 million to $10.56 million and waiting times ranging from 128 to 1173 s. These solutions represent a spectrum of trade-offs between average waiting time and cost and can provide valuable insights for decision-makers in this context. To facilitate further analysis, three distinct solutions within the Pareto front have been identified based on their objective function values. Solutions S1 and S8, which are located on the corners of the Pareto front, represent two extreme solutions whose comparison leads to a meaningful trade-off between cost and waiting time. Solution S1 corresponds to a cost of $5.52 million and an average waiting time of 1173 s, whereas solution S8 corresponds to a cost of $10.56 million and an average waiting time of 128 s. Comparing S1 and S8 indicates that by investing an additional $5.04 million, the average waiting time can be decreased by 1045 s. However, it is necessary to add three new charging stations and install 27 additional charging piles. While it seems capital intensive, such an investment could enhance the user experience and thus it might be deemed reasonable by the stakeholders. An additional noteworthy observation arises from the middle of Fig. 8, where a modest investment results in a significant decrease in the average waiting time, as evidenced by the transition from solution S1 to solution S4. To elaborate further, the cost of implementing the S1 solution is $5.52 million, while the additional investment required to transition to the S4 solution is $1.68 million which is used to install 14 new charging stations. Despite the higher cost, there is a notable reduction in the average waiting time, from 1173 to 470 s, which in turn can improve customer satisfaction and enhance overall operational efficiency. This underscores the need to consider the trade-off between cost and average waiting time in the decision-making process, as small changes in investment can lead to significant improvements in system performance.

To illustrate the importance of DNN in the proposed approach, further experiments were conducted where the waiting times for all solutions in the Pareto front were recalculated solely using the queueing theory (without using DNN). Fig. 9 depicts the waiting times obtained by DNN and the queueing theory formulation, as well as the actual waiting times obtained from the simulation model, along with the percentage difference between the actual waiting times and those approximated by DNN and the queueing theory formulation and provides a visual comparison of the accuracy of DNN and queueing theory formulation in approximating the true average waiting time. Fig. 9 shows that the DNN method has a high predictive performance, with a smaller difference between the predicted and actual values. On the other hand, the approach based on the queueing theory formulation has limitations in capturing the complexity of the waiting process, resulting in an underestimation of the waiting times and a larger estimation error. It is noteworthy to add that relying solely on simulation methods to calculate waiting times can be a time-consuming process. For instance, computing waiting times for each solution in Fig. 9 using the simulation method may take up to 89 s. In contrast, employing a DNN can significantly reduce the computational time needed for this task, as it only takes 0.14 s while still producing results of comparable quality. This highlights the main advantage of using machine learning approaches in accelerating estimated values and reducing computational costs in various applications. These findings highlight the limitations of traditional queueing models in accurately predicting the waiting times for complex problems. Consequently, the integration of advanced DNN becomes crucial in estimating the waiting times of solutions to achieve more accurate results in less computational time.

5.4. Comparison of line-based and FCFS strategies

In this section, the impact of two queue rules to prioritize service offering in charging stations will be investigated: the traditional first-come-first-served (FCFS) strategy, and the line-based strategy, in which charging stations are divided into lines based on the state of charge of the vehicles. It should be added that Appendix C (Table C.1) contains the table for the Pareto front solutions once the FCFS

Table 4
Pareto optimal solutions and their specifications for the line-based strategy.

	Standard NSGA-II				Improved NSGA-II			
Solution Number	Cost ($)	Average waiting time (seconds)	Total number of stations	Total number of piles	Cost ($)	Average waiting time (seconds)	Total number of stations	Total number of piles
S1	5,760,000	1254	4	18	5,520,000	1173	4	16
S2	6,240,000	910	4	22	5,880,000	875	4	19
S3	6,840,000	685	4	27	6,360,000	685	4	23
S4	7,440,000	483	4	32	7,200,000	470	4	30
S5	8,100,000	438	5	30	7,740,000	423	5	27
S6	9,060,000	337	5	38	8,340,000	337	5	32
S7	10,320,000	254	6	41	10,320,000	211	6	41
S8	11,040,000	137	6	47	10,560,000	128	6	43
S9	11,880,000	119	6	54				
S10	12,060,000	89	7	48				

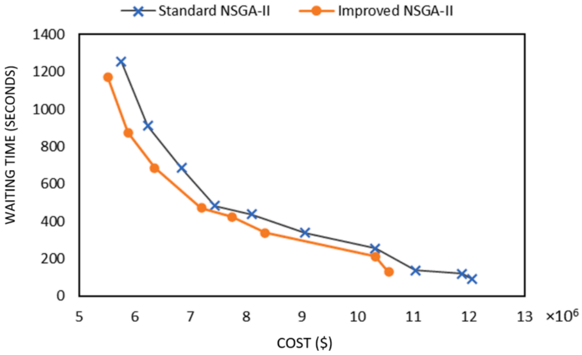

Fig. 8. The comparison of *Standard NSGA-II* and *Improved NSGA-II* using Pareto fronts.

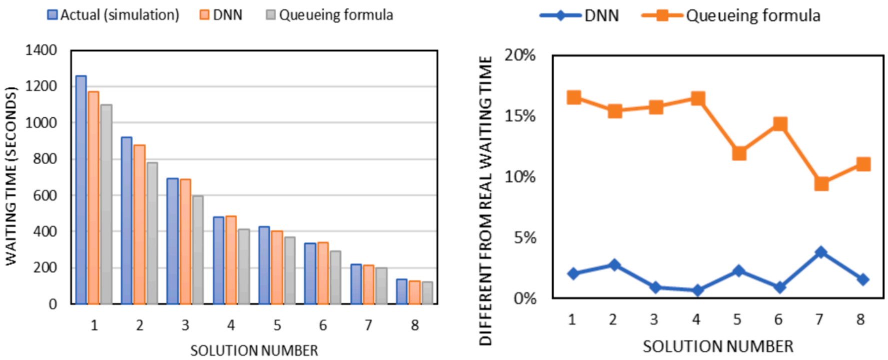

Fig. 9. Waiting time values obtained by DNN, queueing theory, and simulation models for ten solutions in the Pareto optimal front (left), the percentage of difference between results obtained by simulation and DNN for the same solutions (right).

strategy is in place in the charging stations. Two sets of Pareto front solutions were obtained (one for FCFS, and one for line-based) and were shown together in Fig. 10. The results indicate that all the Pareto solutions obtained by the line-based strategy dominate the Pareto solutions obtained by the FCFS strategy, meaning that the line-based strategy outperforms the FCFS strategy in both objectives (i.e., cost and average waiting time) considered in the study. Specifically, for the ten first Pareto solutions (S1 to S8) obtained by each strategy, the average waiting time for overall solutions was averaged. The results indicated that the average of average waiting times for the line-based solutions is significantly lower than the average of average waiting times for FCFS solutions (538 s vs. 1083 s). Also, for any two solutions of the two Pareto fronts with similar cost levels, it can be seen that the line-based Pareto solution comes with a lower average waiting time than the Pareto solution derived from the FCFS.

5.5. Sensitivity analysis

The sensitivity analysis was performed based on three solutions within the Pareto front of line-based strategy to evaluate the impact of SCV of arrival rate and SCV of service rate.

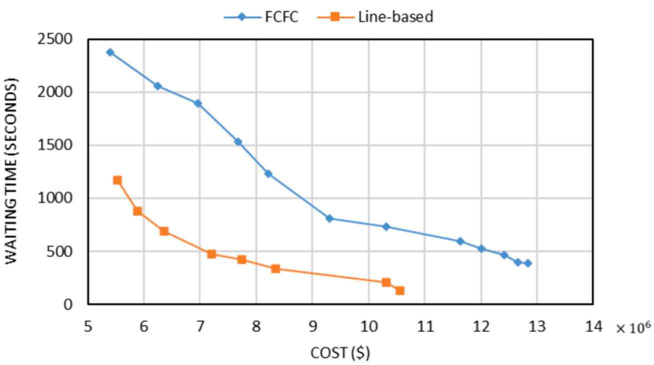

Fig. 10. Pareto solutions for the Line-based and FCFS priority rules.

5.5.1. The effect of squared coefficient of variation (SCV) of the arrival rate

This section summarizes a conducted sensitivity analysis to determine the impact of the SCV of arrival rate on the average waiting time on the proposed model. Ten scenarios were investigated in which the initial SCV of arrival rate for each demand was examined along with an increase in SCV ranging from 5 % to 50 %. The results, depicted in Fig. 11, indicate that increasing the SCV of arrival rate would impact the average waiting time for each solution differently. The highest average waiting time, which is a 2.56 % increase for S1 is experienced with a 5 % increase in the SCV of arrival rate. Simultaneously, a 50 % increase in SCV resulted in a 26.2 % rise in the average waiting time. For solutions with lower average waiting times, such as S4 and S8, the effect of increasing the SCV was more significant. In the case of S4, a 5 % and 50 % increase in SCV resulted in a 3.14 % and 59.75 % increase in the average waiting time, respectively. Similarly, for the S8 solution, which had the lowest average waiting time, a 50 % increase in SCV led to an increase of over 106.67 % in the average waiting time. These findings highlight the significant impact of the SCV of arrival rate on queueing system performance, particularly when a lower average waiting time is desired.

5.5.2. The effect of service rate squared coefficient of variation (SCV)

Similar to the previous subsection, experiments were conducted to analyze the effect of variations in service rate SCV on the average waiting time. Fig. 12 shows that changes in the standard deviation of service rate highly impacts the results such that all three potential solutions (S1, S4, and S8) experienced significant increases in average waiting time, ranging from 226.52 % to 804.44 %. These findings highlight that the variance in service rate, which refers to the variability in the time it takes to recharge an EV, has a significant impact on average waiting time and can lead to longer charging times and potential dissatisfaction among EV drivers. This underscores the importance of minimizing variance in service rate as much as possible. One possible solution to minimize the variance of service rate is fixing the service time for each request, which involves classifying service time based on several factors, such as EV and battery types, as well as charging station specifications. This study partially addressed this issue by assigning a set of service times to each line of charging stations based on the charging level of EVs. However, the findings showed that the service rate variance still has a considerable effect on the average waiting time. Thus, it is important to evaluate the impact of the service rate variance and implement appropriate measures to minimize it, such as establishing fixed service times or utilizing advanced charging technologies that can regulate charging time more precisely.

6. Managerial implications

To build on the research findings, a set of novel managerial implications is proposed for stakeholders in the transportation industry, including city planners, businesses, and governments. First, this study highlights the limitations of traditional queueing models for designing waiting systems. Managers should be aware of the limitations, especially, in complex waiting processes (i.e., systems that management decisions and technological factors could significantly impact the performance). Relying solely on traditional queueing models can lead to an underestimation of actual waiting time and leads to inaccurate time estimation. Second, this study highlights the role of AI-based methods in optimizing logistics and operation decisions. Among potential innovative AI-based applications, this paper presents two novel methods for the estimation of waiting times at charging stations and improvement of metaheuristic algorithm to solve the mathematical model. The integration of advanced DNN models into waiting time estimation could enhance the accuracy of time estimation in systems with limited resources. In addition, by improving the NSGA-II algorithm using the deep neural network, the quality of solutions is also enhanced considerably. These two applications prove that there are many ways to apply AI to improve the operations in a firm in a competitive market (Li et al., 2021; Luo et al., 2019).

Other findings demonstrate that a relatively small investment in additional charging stations can lead to a substantial reduction in average waiting time which improves overall customer satisfaction and operational efficiency. Thus, decision-makers should carefully consider the trade-offs between cost and system performance when evaluating potential solutions. This study emphasizes the importance of considering solutions beyond the minimum cost option, as more investment in charging station infrastructure can improve the performance of such stations and promote the adoption of EVs in society. By balancing cost and system performance, network planners can ensure offering an acceptable level of service for EV drivers while maintaining the cost-effectiveness of their operation.

Furthermore, the study identifies the impact of changes in the standard deviation of arrival and service rates on the average waiting

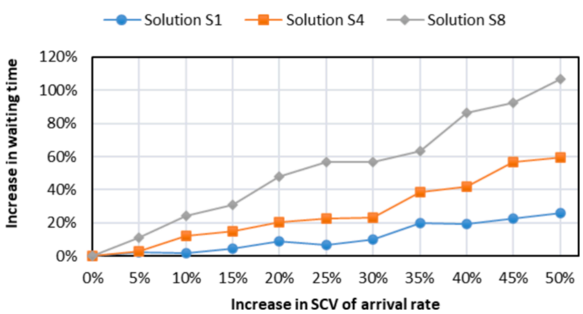

Fig. 11. The effect of SCV of arrival rate on waiting time.

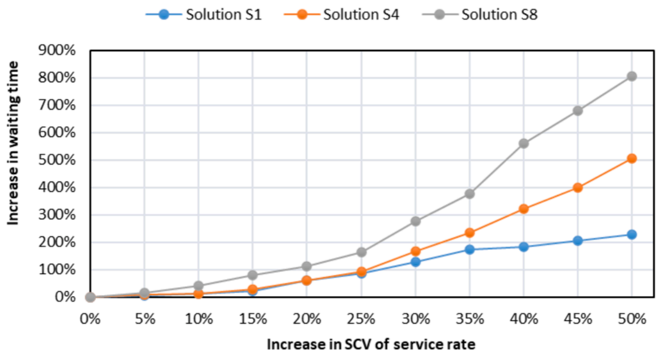

Fig. 12. The effect of SCV of service rate on waiting time.

times. The results suggest that the SCV of arrival rate can significantly impact queueing system performance, particularly in situations where lower average waiting times are preferable. Additionally, variations in the service rate significantly affect the average waiting time and can result in extended charging durations and driver dissatisfaction. Therefore, the decision-makers should carefully assess the influence of service rate variance on the system performance. Managers should take suitable measures, such as establishing fixed service times or utilizing advanced charging technologies, to regulate charging time in a precise manner.

The FCFS strategy has been widely used in previous studies to prioritize offering charging services to EVs in charging stations. However, the line-based strategy proposed in this paper provides solutions with lower cost and lower average waiting time than those of the FCFS strategy. It should be noted that while a line-based strategy provides better results than FCFS, its implementation might come with practical challenges. For instance, categorizing EVs upon arrival at the charging station may lead to situations where an early-arriving EV with higher charging needs waits longer to start charging than a later-arriving EV. Thus, incentivizing the drivers to participate in the line-based strategy would call for developing a rewarding mechanism in which drivers receive concrete benefits by giving up on their priorities to help lower the overall average waiting time.

7. Conclusions

This study proposes a hybrid solution for the charging station location-capacity problem where charging rates are probabilistic with general probability distributions. The proposed approach simultaneously determines the location and capacity of charging stations (i.e., number of charging piles), and assigns piles to electric vehicles based on their level of charge, by minimizing the total costs and average waiting time, simultaneously. The approach integrates a queueing model with mixed integer non-linear programming (MINLP) and uses a DNN technique to accurately estimate waiting time.

Computational experiments confirmed that DNN exhibits strong predictive performance, closely matching true values, in contrast to traditional queueing models. This study highlights the limitations of these models in estimating waiting times for complex $GI/GI/c$ queueing systems. To enhance accuracy, this paper suggests integrating advanced DNN techniques into the optimization framework. The research underscores the significance of variability in arrival and service rates in determining waiting times. The analysis reveals that service rate variability has a greater impact than arrival rate variability. Even a slight increase in service rate variability significantly escalates waiting times, emphasizing the importance of managing service rate variability to reduce EV waiting times and enhance service satisfaction. Furthermore, computational experiments showed that a 30 % increase in infrastructure investments could lead to a 2.5-fold reduction in waiting times across the network and overall system improvements.

The conducted experiments were based on a real case in Halifax, Canada. As a result, the proposed planning methodology could provide stakeholders (e.g., city planners, investors, and other interested parties) with a practical solution to plan for EV charging stations. The methodology facilitated the identification of optimal charging station locations and the allocation of the appropriate number of recharging piles and waiting spaces for each station.

Future research should delve into optimizing charging station locations across extended time periods as EV charging networks evolve. These models should consider factors like waiting times, operational constraints, budget limitations, and evolving user preferences. This will empower decision-makers in creating transportation networks that align with community needs and support sustainable transport. Additionally, addressing the non-convex and MINLP nature of the model and the complexity of extracting waiting times from a DNN presents challenges for standard solvers. While metaheuristic algorithms offer viable solutions, future studies could explore exact optimization methods or hybrid approaches, combining the strengths of both exact and metaheuristic algorithms to potentially achieve improved results.

As another research direction, while research has predominantly focused on scenarios involving full EV charges upon arrival at charging stations, it is imperative to address partial charging strategy as well. Future research can also explore strategies to reduce service rate variability at charging piles, aiming to enhance service time predictability and improve overall satisfaction among EV drivers. Moreover, it is recommended to investigate multiple routes and consider travelers' equilibrium behaviors in which travel time and queuing time are regarded as the two primary factors in route selection. This approach would significantly improve our comprehension of the impact of charging station queuing times on the optimization of charging station location problems. Finally, when it comes to actual implementation, effective policies and mechanisms should be designed to facilitate drivers' involvement and eventually lead to a more successful implementation of line-based strategy while maintaining a sense of fairness among drivers.

CRediT authorship contribution statement

H. Pourvaziri: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **H. Sarhadi:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **N. Azad:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **H. Afshari:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **M. Taghavi:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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

Data will be made available on request.

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Appendix A

There are many different optimization algorithms available for training neural networks. To identify the best optimizer for the DNN, experiments were performed on various popular optimization algorithms, as outlined below:

- Stochastic gradient descent (SGD) (Robbins and Monro, 1951): SGD is a widely utilized optimization algorithm that modifies the model's parameters iteratively based on the gradient of the loss function. It randomly selects a batch of data points, calculates the gradient of the loss function with respect to the parameters for that batch, and updates the parameters in the direction opposite to the gradient to minimize the loss function.
- Adagrad (Duchi et al., 2011): Adagrad is an adaptive optimization algorithm that adjusts the learning rate of each parameter using historical gradient information. Specifically, Adagrad reduces the learning rate for parameters that exhibit a high historical gradient, whereas it increases the learning rate for those with a low historical gradient. This technique can be advantageous in situations where the data comprises sparse features.
- Adadelta (Zeiler, 2012): Adadelta is a variation of the Adagrad optimization algorithm that addresses the issue of the learning rate continuously decreasing. It achieves this by utilizing a moving window of gradients and parameter updates, instead of considering the entire history. This approach enables Adadelta to converge more quickly in certain scenarios.
- RMSProp (Tieleman and Hinton, 2012): RMSProp is an adaptive optimization algorithm that modifies the learning rate of each parameter by utilizing a moving average of the squared gradient. It shares similarities with Adagrad in terms of reducing the learning rate for parameters with high historical gradients and increasing it for parameters with low historical gradients. However, RMSProp incorporates an exponentially decaying average of the squared gradient to prevent the learning rate from becoming overly small, distinguishing it from Adagrad.
- Adam (Kingma and Ba, 2017): Adam is a popular optimization algorithm that combines the advantages of AdaGrad and RMSProp. Adam utilizes adaptive learning rates for each parameter that are derived from the gradients' first and second moments. This allows the algorithm to converge quickly and effectively in high-dimensional parameter spaces.

The prediction accuracy of each optimizer was evaluated using two standard metrics including MSE and coefficient of determination (R^2). R^2 measures the predictive performance of the model, while MSE quantifies the average squared deviations from the actual values. The R^2 and MSE are defined by Eq. (A.1) –(A.3).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\widehat{y}_i - y_i)^2}{\sum_{i=1}^{N}(\overline{y} - y_i)^2} \tag{A1}$$

$$\overline{y} = \frac{\sum_{i=1}^{N} y_i^p}{No} \tag{A2}$$

$$MSE = \frac{1}{No}\sum_{i=1}^{N}(\widehat{y}_i - y_i)^2 \tag{A3}$$

where No denotes the sample size and $\widehat{y}_i$ and y_i are the prediction and true values, respectively. Fig. A.1 illustrates the performance of various optimizers based on their MSE values on the training and validation sets. The results indicate that the Adam optimizer achieved the lowest MSE for both sets. The convergence of the MSE values suggests that the model is well-fitted without the issues of overfitting or underfitting. In addition, Fig. A.2 demonstrates a scatterplot of the predicted and observed values for all the optimizers. The blue line represents the reference line for matching predicted and actual values. Most plots for all optimizers are concentrated around the blue line. However, the Adam optimizer demonstrated the best performance, with the highest R^2 value, indicating that it would be the optimal choice for training the DNN. Therefore, the Adam optimizer was selected for training the DNN. Fig. A.2 shows that the Adam optimizer can attain convergence within 50 epochs, which is the selected number of epochs for the DNN. Initial experiments were conducted to determine the optimal configuration of the DNN model, including the number and dimensions of hidden layers, as well as the ideal batch size.

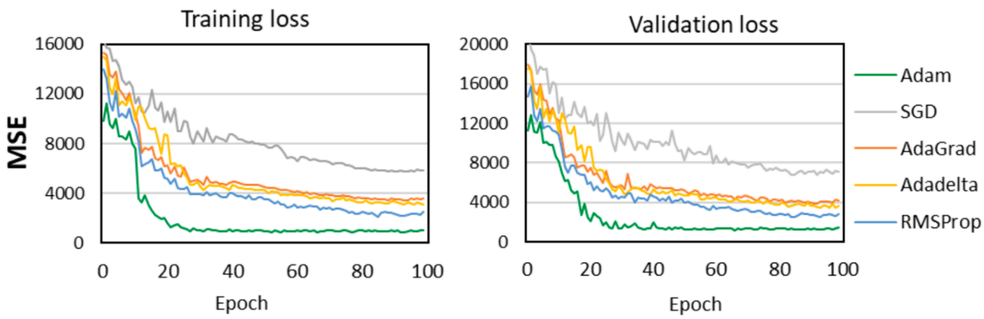

Fig. A1. Training (left) and Validation (right) losses of optimizers.

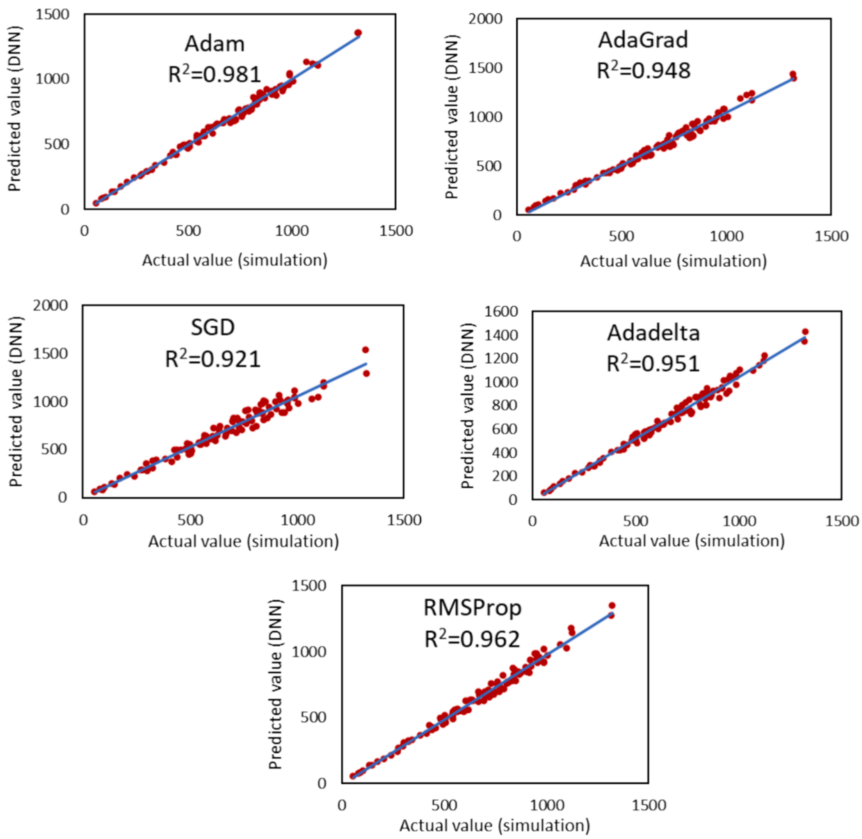

Fig. A2. Scatterplots of the optimizers for the dataset.

Appendix B

The Mean Ideal Distance (MID) serves as a key metric for assessing the efficiency of an algorithm. This criterion measures the distance of solutions on the Pareto front from an ideal point, typically situated at (0, 0) in a two-dimensional graph. The MID is computed using the following formula:

$$MID = \frac{1}{NOS}\sum_{i=1}^{NOS}\sqrt{\left(f_{1,i} - f_{1,\ ideal}\right)^2 + \left(f_{2,i} - f_{2,\ ideal}\right)^2} \tag{B1}$$

where $f_{1,i}$ and $f_{2,i}$ are the value of the first and second objective function for solution i, and $f_{1,\ ideal}$ and $f_{2,\ ideal}$ are the ideal value for objective functions. *NOS* is number of solutions in the pareto front. Within the scope of this research, where the objective functions prioritize minimization, a reduced MID value indicates enhanced algorithm performance. As per the results, the MID has decreased from 8,874,000 to 7,740,000, indicating a noteworthy 12.77 % enhancement in the MID metric. This demonstrates a significant improvement in the quality of the solutions.

Appendix C

Table C1
Pareto optimal solutions and their specifications for the FCFS strategy.

Solution Number	Cost (S)	Average waiting time (Seconds)	Total number of stations	Total number of piles
S1	5,400,000	2377	4	15
S2	6,240,000	2055	4	22
S3	6,960,000	1895	4	28
S4	7,680,000	1529	4	34
S5	8,220,000	1235	5	31
S6	9,300,000	809	5	40
S7	10,320,000	728	6	41
S8	11,640,000	593	6	52
S9	12,000,000	524	6	55
S10	12,420,000	467	7	51
S11	12,660,000	395	7	53
S12	12,840,000	387	8	47

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