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RESEARCH ARTICLE

A Charging Strategy for Large Commercial Electric Vehicle Fleets

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ABSTRACT The popularity of Commercial Electric Vehicles (CEVs) has experienced a surge in recent years, particularly in urban vocational contexts, as a means of advancing towards the goal of attaining net-zero emissions by 2050. The return-to-base charging strategy, which involves charging CEVs at depots, has become a prevalent practice for smaller CEV fleets. Nevertheless, for larger CEV fleets, the limited charging capacity at depots presents a significant challenge, leading to a reliance on both limited depot charging infrastructure and public charging infrastructure. This reliance can have a substantial impact on both the operational costs and the sustainability of logistics services. To address these challenges, this study proposes a new charging strategy for managing the charging of large CEV fleets. The proposed strategy coordinates the charging of CEVs at depots and public charging stations. The strategy is formulated as a constraint optimization problem and takes into consideration operational schedules, demand charges, and the characteristics of public charging stations. The results of this study demonstrate the effectiveness of the proposed strategy in optimizing CEV charging at different stations, preserving the continuity of logistics services, and reducing total travel costs by 30% compared to existing solutions. This study offers a solution to the challenges faced by large CEV fleets in their efforts to achieve cost-effective and sustainable charging solutions.

INDEX TERMS Heavy commercial electric vehicles, return-to-base, transportation, vehicle routing, vehicle-to-grid, optimization, peak demand, electric trucks.

NOMENCLATURE

ABBREVIATION

AS	Allocation Schedule.
CEV	Commercial Electric Vehicle.
OSLS	Operational Schedules during Logistic Services.
OSPT	Operational Schedules during parkigng Times.
SoC	State of Charge.

PARAMETERS AND VARIABLES

$T^{Ch}_{n,i}$	Charging time of nth CEV at public station i.
$T^{max}_{n,i}$	Maximum charging time at public station i.
$T^{min}_{n,i}$	Minimum charging time at public station i.
E^{Cap}	Energy capacity of CEV.
$\bar{t}^{End}_{n}$	Shifted ending time of charging due of OSPT.
Γ	Set of charging schedules at public stations.
$\mathcal{AI}_{n,t}$	Availability index of nth CEV at time slot t.
Ω	Set of generated feasible solutions.
$\overline{\overline{W}}$	Set of CEVs assigned to depot stations with partial charging.
$\overline{V}$	Set of customer excluded due to $\overline{W}$.
$\overline{W}$	Set of CEVs excluded from logistic service.
Φ_{Λ}	Set of routes contained in solution Λ.
ρ_c	Cost of not serving one customer.
ρ_D	Cost per unit of distance.
ρ_d	Demand cost of depot charging.
$\rho^{P}_{i,t}$	Energy pricing rates of station i at time t.

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ρ_t^D	Energy pricing rates of depot station.
ρ_v	Cost of running one vehicle.
C_D	Total charging cost at depot stations.
C_P	Total charging cost at public stations.
C_T	Overall cost of logistics services.
Ch_n	Minimum charging time of nth CEV at depot station based on P_{max}.
d_{ij}	Travel distance between customers i and j.
E_{Depot}	Total energy to charge all CEVs at depot.
$E_{i,n}^P$	Total energy charged in nth CEV at public station.
E_i	Remaining energy at arrival to node i.
E_n^D	Energy charged in nth CEV at depot station.
E_n^I	Initial energy at arrival to depot for vehicle n.
E_n^{near}	Required energy of CEV to reach nearest station.
E_{Public}	Total energy charged in nth CEV along route.
$E_{v_0,n}^R$	Remaining energy at departure from depot.
F	Set of public charging stations.
L_i	Earliest arrival time of customer i.
P_i	Charging power of station i.
P_{max}	Power capacity of depot station.
$P_{n,t}^{De}$	Charging rate of nth CEV at depot station.
r	Energy consumption of CEV.
S	Set of depot charging stations.
T_i^{Se}	Service time at customer i.
T_{ij}^{Tr}	Travel time between nodes i and j.
T_i^{Ar}	Arrival time at node i.
T_i^{Le}	Leaving time from node i.
T_i^{Pl}	Plug time at station i.
T_i^W	Waiting time at station i.
t_n^{End}	Ending time of charging nth CEV at the depot.
t_n^{Finish}	Finish time of OSPT of nth CEV.
$t_n^{Operate}$	Start time of OSPT of nth CEV.
t_n^{Start}	Starting time of charging nth CEV at the depot.
U_i	Latest arrival time of customer i.
V	Set of customers that need to be serviced.
V''	Set of all vertices including stations.
v_0, v_{N+1}	Depot nodes.
v_i	Customer i node.
W	Set of CEVs used in logistic service.
x_{ij}	Decision variable of route selection.

I. INTRODUCTION

Many governments have set targets and policies for zero-emission vehicles by 2030 and 2040 in order to achieve net-zero carbon emissions and meet global climate goals by 2050 [1], [2], [3]. In response to this, there has been an increase in the electrification of commercial vehicles with gross vehicle weights ranging from 3.5 to 15 tonnes [4]. A wide variety of applications can be achieved through the use of these vehicles, including long-haul and vocational work applications [5], [6], [7]. Commercial vehicles used in vocational work applications, such as urban freight and delivery vehicles, are more suited to be electrified because of their limited weight and range, and their potential for overnight charging [1], [5], [8], [9]. In such applications, CEVs operate according to operational schedules during logistics services provided to customers. Thus, many logistic service providers, such as UPS, DHL, JD, Walmart Inc, FedEx, Anheuser-Busch, Amazon, and TNT have incorporated CEVs into their fleets [5], [9], [10].

During the early stages of CEV adoption, CEVs are commonly charged at the depot using a "return-to-base" strategy, where a charging station is dedicated to each CEV so that it can be charged overnight or between shifts [11], [12], [13]. The public charging of CEVs along routes may be necessary for applications with longer routes and also to provide ancillary services to the grid [12], [14], [15], [16], [17]. However, as the adoption of EVs in the fleet increases, the existing power infrastructure may be unable to accommodate the additional capacity and thus the number of charging stations in the depot [11], [18]. Adding charging stations will require upgrading depot networks and distribution grids, which is a costly and time-consuming undertaking [1], [19]. To reduce the capital cost of network upgrades and facilitate the adoption of CEVs, it is necessary to allow a number of CEVs to share existing charging stations at the depot, as depicted in Fig. 1 [11], [20]. For this to happen, the charging process for CEVs must be coordinated properly to determine the proper allocation of CEVs to the depot stations and their charging starting times.

The charging of CEVs at depots also presents challenges related to the peak demand for charging loads and the demand costs that are applied to commercial and industrial locations in addition to the energy charge [21]. It is therefore important to coordinate the CEV charging at the depot so that this impact is minimized to reduce the increase in depot charging costs [21], [22], [23]. Furthermore, CEV charging at the depot can be affected by the special operational schedules during parking time (OSPT), during which CEVs are moved for maintenance, washing, and loading the next day's cargo [11], [24]. These schedules significantly affect the charging of CEVs, both in terms of the period for charging and the time at which charging starts. Depending on the duration of OSPT, CEVs may need to be reallocated to different depot stations after returning from OSPT.

The challenges of depot charging may affect the fulfillment of CEVs' energy requirements at the depot; thus, public charging infrastructure is essential to maintain the continuity of CEVs during logistics services [12]. Public charging stations differ according to their location, charge power rates, wait times, and TOU tariffs [25], [26], [27], [28], [29]. It is important to consider these variants when scheduling CEV charging at public charging stations in order to ensure the lowest possible charging costs. Since CEVs charge at public stations while providing logistics services, routes used to

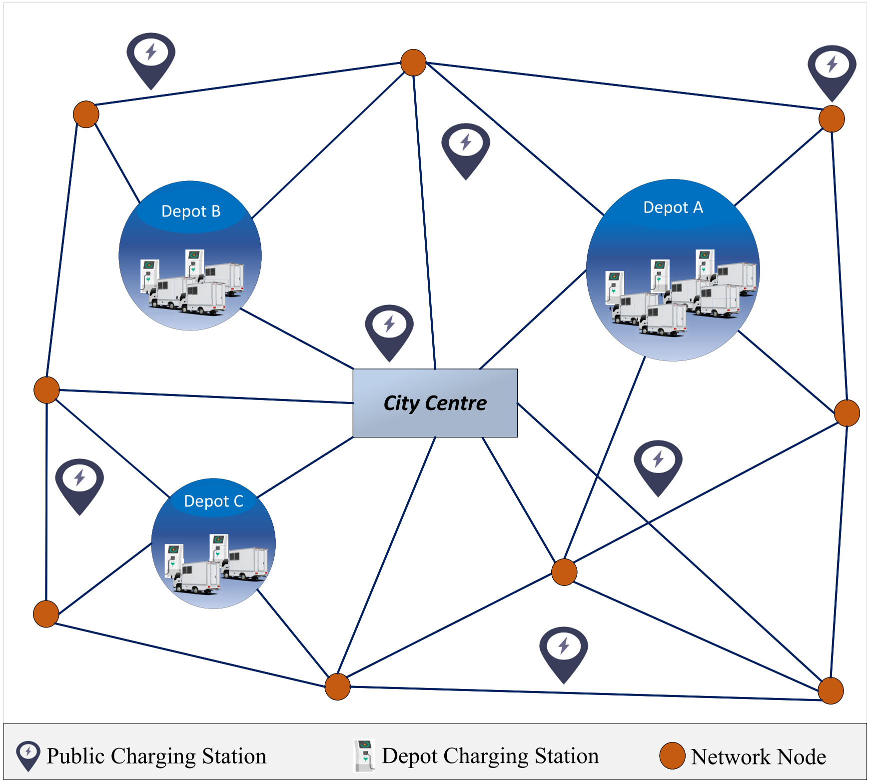

FIGURE 1. CEV charging at public and depot charging stations.

reach the public stations should be as short as possible to reduce the overall travel distance and the logistics company's costs [5], [12].

In the literature, researchers have presented several charging systems which are intended to manage the charging of EVs fleet at parking locations. Authors in [30] presented a charging strategy for coordinating the EV charging at different types of charging stations installed in parking lots. The proposed strategy assigns EVs to the charging stations, then uses a charging algorithm to determine when it should be charged. Reference [31] developed a charging system for EVs at parking locations based on real-time optimization. In this algorithm, a peak load limitation-oriented demand response program is proposed along with the objective of maximizing the load factor of the EV on a daily basis. In [21], a real-time charging algorithm was proposed for EVs at commercial charging locations. A key objective of this strategy is to reduce the demand charges for charging station hosts as well as to accommodate local and utility demands. In [22], a smart charging system is proposed that coordinates the charging of commercial EVs at their depots. The proposed system aims to minimize depot station demand charges while taking into account the operational conditions of EVs during parking periods. In the previous works, however, parking locations were assumed to have sufficient charging stations for each vehicle that arrived. Furthermore, these studies assumed EVs had sufficient battery banks to accomplish their trips and return to their parking locations, so public charging was not taken into account.

Several studies [32], [33], [34], [35] have proposed smart charging strategies for EVs at public charging stations that took into account charging times, travel timess, waiting times, and charging costs. Nevertheless, these studies did not take into account the charging problems associated with CEVs and their OSLS. To consider OSLS of CEVs, many works in literature have incorporated the CEVs public charging problem into the vehicle routing problems [36], [37], [38], [39], [40], [41] to ensure the continuity of CEVs during logistic services. Yang et al. [42] developed a model for solving the routing and CEV charging at public stations simultaneously, taking public station characteristics, time window, and battery size into account. Authors in [43] introduced a mixed heuristic algorithm to solve routing and CEV charging for large-scale distribution problems. In [44], a bi-objective bilevel programming framework was developed to identify the location of charge stations, with the goal of minimizing travel time and charging costs. Wang et al. [45] have included public stations' detours in optimizing the routes of CEVs to consider the importance of charging stations' location. The optimization model also considered real-time traffic data and the cost of regenerative braking. In [46], a two-stage simulation-based heuristic based on Adaptive Large Neighborhood Search was proposed to optimize the routing of CEVs and charging at public stations with stochastic waiting times. In stage one, routes are determined by using expected waiting times at the stations, while stage two penalizes time-window violations and late returns to the depot in order to correct the infeasible solution.

To include the variable energy consumption, Authors in [47] and [48] have proposed an optimization model for CEV routing considering dynamic energy tariffs and energy consumption of CEVs. The energy consumption model in these studies enabled the partial charging of CEVs at public stations to ensure that a given vehicle would not run out of charge along the route. Authors in [49] and [50] have investigated the public charging of CEVs when charging stations provides both battery swapping and fast charging for CEVs. In their studies, CEVs may be charged fully or partially in accordance to the energy requirements and time windows constraints. The CEV charging at depot charging stations has an impact on optimizing routes and public charging of CEVs, thus should be considered [5]. Thus, the authors of [10] proposed a bi-level optimization model to solve the routing and charging problems of CEVs at different charging stations along its route, including the depot. The max-min ant system algorithm is used to generate fixed feasible routes at the upper level. A heuristic algorithm was then developed to optimize CEV charging at public and depot stations. In [51], vehicle-to-grid (V2G) services and the stochastic demand of charging stations have been taken into account in routing and charging problems. The study scheduled the CEV charging at public and depot stations based on routing problem constraints. An optimal solution was reached by combining a custom Genetic Algorithm (GA) with embedded Markov decisions and trust region optimization methods.

In our previous work [12], we investigated the possibility of using public charging stations in addition to depot charging for small CEV fleets. In [12], we assumed that a depot would have enough charging stations for every arriving CEV, which would also be available for charging during the entire parking period. The assumption applies to depots with a small fleet of CEVs whose OSPT periods do not interfere with their charging cycles. The work in [12], however, is inadequate for large CEV fleets and/or depots with a limited number of charging stations.

As discussed above, the charging and routing problems for CEVs have been studied in the literature with various algorithms proposed to address these issues. However, a significant gap in literature remains in regards to the efficient charging of large CEV fleets at depots with limited charging infrastructure. The existing literature has mainly focused on the immediate accessibility of charging stations for each CEV that reaches the depot. However, it is well-established that upgrading the power infrastructure to accommodate the addition of charging stations for a large fleet of CEVs at each depot is expensive and not practical in many cases. Additionally, there is a lack of research on the impact of operational schedules during CEV parking times on the charging process. Thus, it is imperative to consider these variants in optimizing the routing and charging problems for large CEV fleets to achieve cost-effectiveness and continuity of logistics services.

This paper aims to address the previously mentioned gap in the literature by proposing a new charging strategy. This strategy aims to resolve the charging and routing problems of large CEVs fleets at depots and public charging stations. The goal of the proposed strategy is to maximize the benefits for logistics providers by reducing total travel costs and ensuring the continuity of logistics service. The main contributions of this paper are:

1) To the best of the authors' knowledge, this paper is the first of its kind that coordinates the charging process of a large CEV fleet at both depots with limited charging infrastructure and public charging stations, while taking into account the operational schedules of the CEVs during parking times and the provision of logistics services.
2) The proposed charging strategy provides a systematic and optimal approach to allocate and manage the charging process of the large CEV fleet at depots, thereby effectively utilizing the limited charging infrastructure among the CEV fleet.
3) The strategy incorporates multiple variants of the CEV charging problem, including the costs associated with peak demand at depots, the locations, delays, and characteristics of public charging stations, and partial recharging of CEVs.
4) This paper also evaluates the impact of various variants for charging the large CEV fleet at both depots and public charging stations on the routing problem of these vehicles, with the aim of enhancing the benefits for logistics providers.

This paper is organized as follows. In Section II, the mathematical model formulation is introduced. In Section III, the proposed strategy is illustrated. Section IV presents results and performance analyses. The conclusion of the paper is presented in Section V.

II. MATHEMATICAL MODEL FORMULATION

A. PROBLEM DEFINITION

This paper addresses the problem of charging a set of CEVs with a limited number of charging stations installed at their depot while also dealing with the routing and public charging problems for the CEVs. Let W be the set of CEVs used to service the set of customers $V = \{v_1, v_2, v_3 \cdots, v_N\}$. During the driving cycle, the vehicles depart from the depot (v_0) and serve several customers in accordance with OSLS before returning to the depot (v_{N+1}). The OSLS of CEVs define the service time (T_i^{Se}) a CEV spends servicing the customer as well as the time windows (L_i, U_i) at which the customer should be serviced, where L_i represents the customer's earliest arrival time and U_i represents the customer's latest arrival time. To maintain operational schedules, CEVs preferred to be charged at depot charging stations $S = \{s_1, s_2, s_3 \cdots, s_M\}$ with the energy required to complete their daily driving cycles. Increasing adoption of CEVs may exceed the number of charging stations in the depot due to power constraints and capital costs of charging infrastructure. Therefore, CEVs should be able to share chargers at the depot by scheduling charging times optimally. Let t_n^{Start} and t_n^{End} denote the starting and ending time of charging nth CEV at the depot that satisfies

$$t_n^{AR} \leq t_n^{Start}, t_n^{End} \leq t_n^{DP} \tag{1}$$

where t_n^{AR} and t_n^{DP} denote the arrival and departure times of nth CEV at the depot. Hence, the charging period of nth CEV can be represented by availability index as follow

$$\mathcal{AI}_{n,t} = \begin{cases} 1, & t \in [t_n^{Start}, t_n^{End}] \\ 0, & Otherwise \end{cases} \quad \forall t \in \mathcal{T}, \forall n \in W \tag{2}$$

where $\mathcal{T} = \{1, 2, 3, ...\}$ indicates the set of time slots of length Δt that divide CEV dwell periods at depot. When CEVs have OSPT that overlap with their charging times, their availability index should be updated. Let $t_n^{Operate}$ and t_n^{Finish} indicate the start and finish times of the OSPT of nth CEV, then $\mathcal{AI}_{n,t}$ is updated as follows

$$\mathcal{AI}_{n,t} = \begin{cases} 1, & t \in [t_n^{Start}, t_n^{Operate}] \\ 1, & t \in [t_n^{Finish}, \bar{t}_n^{End}] \\ 0, & Otherwise \end{cases} \quad \forall t \in \mathcal{T}, \forall n \in W \tag{3}$$

where $\bar{t}_n^{End}$ represents the shifted ending time of charging nth CEV because of OSPT. Due to the simultaneous charging of CEVs, the peak demand of a depot increases significantly compared to the base-load demand. In turn, this increases peak demand costs, which are much higher than energy costs for commercial enterprises. Optimizing the power rates of charging stations can mitigate the impact of peak demand on CEV charging costs at depots. Let $P_{n,t}^{De}$ represents the decision variable for the charging power rate of nth CEV at time $t \in \mathcal{T}$, which is defined as follows

$$0 \leq P_{n,t}^{De} \leq P_{max} \tag{4}$$

P_{max} is the power capacity of depot station. Energy charged in the *nth* CEV at the depot station is calculated as follows

$$E_n^D = \sum_{t \in \mathcal{T}} P_{n,t}^{De} \cdot \mathcal{AI}_{n,t} \cdot \Delta t \tag{5}$$

Thus, the total energy required to charge all CEVs at depot stations is defined as

$$E_{Depot} = \sum_{n \in W} E_n^D \tag{6}$$

CEV charging at depot stations may increase the peak demand of the aggregate load profile at the depot, which is composed of the base load profile and the total charging load profile. let P_t^{Ba} indicates the base-load power of the depot at time slot $t \in \mathcal{T}$. The increase in peak demand of depot load profile can be expressed as follows

$$P_{Depot} = max\{P_t^{Ba} + \sum_{n \in W} (P_{n,t}^{De} \cdot \mathcal{AI}_{n,t}) : t \in \mathcal{T}\} - max\{P_t^{Ba} : \forall t \in \mathcal{T}\} \tag{7}$$

Increasing the adoption of CEVs in the depot and strict operation schedules during parking times can limit the energy that can be charged in CEVs at depot charging stations, requiring charging of these vehicles at public charging stations $F = \{f_1, f_2, f_3 \cdots, f_M\}$. A public charging station can differ in terms of its charging power rate, location, energy costs, and waiting time. Charging CEVs at public stations should therefore be scheduled in such a way that both the charging time and cost are minimized. Let $T_{i,n}^{Ch}$ be the decision variable for the charging time of the *nth* CEV at the public station, which is defined as

$$T_{i,n}^{min} \leq T_{i,n}^{Ch} \leq T_{i,n}^{max} \quad \forall i \in F \tag{8}$$

where $T_{i,n}^{min}$ and $T_{i,n}^{max}$ define the limits for the minimum and maximum charging times at the station respectively. The total energy charged in *nth* CEV at public station $i \in F$ is calculated as follows:

$$E_{i,n}^P = \int_{T_i^{Pl}}^{T_i^{Pl} + T_{i,n}^{Ch}} P_i \quad dt \tag{9}$$

P_i represent the power capacity of the public station i, and T_i^{Pl} represents the plug time of CEV at the station. T_i^{Pl} is calculated based on the arrival time (T_i^{Ar}) and the waiting time (T_i^W) of CEV at station i, where $T_i^{Pl} = T_i^{Ar} + T_i^W$. The total energy charged in *nth* CEV along its driving cycle defines as

$$E_{Public} = \sum_{n \in W} \sum_{i \in F} E_{i,n}^P \tag{10}$$

In addition to the energy charged at depots, the energy charged at public stations should be sufficient to complete the driving cycle of a CEV. The lack of public charging stations along specific routes and time window constraints may result in insufficient energy being charged in CEVs, resulting in many consumers being left out. Let $\overline{W}$ represent the set of CEVs that do not receive the required amount of energy from public and depot charging stations, where $\overline{W} \subset W$. As a result of the CEVs in $\overline{W}$, a set of customers $\overline{V} \subset V$ are not serviced. Maximizing logistics company profits requires minimizing customers in $\overline{V}$ and therefore CEVs in $\overline{W}$. This can be achieved by solving the routing problem of CEVs to find routes with sufficient public stations while still meeting OSLS.

The goal of solving CEV routing problems is to select the routes that maximize logistics companies' benefits. Routes for CEVs should be optimized in terms of travel distance and availability of public charging stations so that trip costs can be reduced and logistics services will not be disrupted. let $V' = V \cup F$ represents the set of all costumers and public charging stations nodes, and $V'' = V' \cup v_0 \cup v_{N+1}$ indicates the set of system nodes including depot. Any route between two nodes i and j is determined by the binary variable xij, which is defined as follows

$$x_{i,j} = \begin{cases} 1, & \textit{If route i to j is selected} \\ 0, & \textit{Otherwise} \end{cases} \tag{11}$$

Considering feasible paths between customers and detour distances to reach charging stations, the total distance (D_T) of the trip can be calculated as follows

$$D_T = \sum_{i,j \in V''} (d_{ij} \cdot x_{ij}) \tag{12}$$

$d_{i,j}$ denotes the travel distance between nodes $i, j \in V''$. Routes between a depot and all other nodes determine the number of vehicles that will be used to provide the logistic services. The number of vehicles leaving the depot can be calculated as follows

$$|W| = \sum_{j \in V''} x_{0j} \tag{13}$$

Considering that there may be insufficient energy charged in CEVs as a result of a lack of public charging stations, the number of CEVs which complete their drive cycle can be calculated as follows

$$Z = |W| - |\overline{W}| \tag{14}$$

B. PROBLEM FORMULATION

This paper aims to maximize the benefits of logistic companies operating fleets of CEVs by optimizing their routing and charging with a limited number of charging stations located at depots and public locations. Therefore, the objective function of the optimization problem can be formulated to minimize the overall cost (C_T) of logistics services as follows

$$\begin{aligned} Min\ C_T &= D_T \cdot \rho_D + Z \cdot \rho_v + |\overline{V}| \cdot \rho_c \\ &\quad + E_{Public} \cdot \rho^P_{i,t} + E_{Depot} \cdot \rho^D_t + P_{Depot} \cdot \rho_d \end{aligned} \tag{15}$$

As shown in (15), the overall cost of logistics services can be broken down into six terms. The first term represents the cost of distance traveled by all CEVs, where ρ_D is the cost per unit of distance. In the second term, the cost is related to running the vehicles used to service all customers, where ρ_v represents the cost per vehicle. The cost in the third term is associated to the number of unserviced customers, where ρ_c represents the cost of not providing services to one customer. In the fourth and fifth terms, the energy cost associated with charging CEVs at public and depot stations is indicated. $\rho^P_{i,t}$ and ρ^D_t are the energy pricing rates for public and depot stations, respectively. The last term indicates the cost of increase in the peak demand of depot and ρ_d is the demand charge rate. The following constraints are subject to objective function in (15):

$$E^R_{v_0,n} = E^D_n + E^I_n, \ \forall n \in W \tag{16}$$

$$E^{near}_n \leq E^R_{v_0,n} \leq E^{Cap}_n, \quad \forall n \in W \tag{17}$$

$$E^{near}_n = min\{(d_{0,j} \cdot r) \ \ \forall j \in F\} \tag{18}$$

$$E^R_{i,n} \geq 0 \quad \forall i \in V'' \tag{19}$$

$$E^R_{j,n} = \begin{cases} E^R_{i,n} - (d_{i,j} \cdot r), \\ \quad \forall i \in V''|F, \forall j \in V''|v_0, x_{ij} = 1 \\ E^R_{i,n} + E^P_{i,n} - (d_{i,j} \cdot r), \\ \quad \forall i \in F, \forall j \in V''|v_0, x_{ij} = 1 \end{cases} \tag{20}$$

$$E^R_{i,n} + E^P_{i,n} \leq E^{Cap}_n \quad \forall i \in F, n \in W \tag{21}$$

$$\sum_{j \in V'', i \neq j} x_{i,j} = 1 \quad \forall i \in V \tag{22}$$

$$\sum_{i \in V''} x_{i,j} - \sum_{i \in V''} x_{j,i} = 0 \quad \forall j \in V'' \tag{23}$$

$$\begin{aligned} Q_j \leq Q_i - c_i x_{i,j} + C(1 - x_{i,j}) \\ \forall i \in V''|v_{N+1}, \forall j \in V''|v_0, i \neq j \end{aligned} \tag{24}$$

$$0 \leq Q_i \leq C \quad \forall i \in V'' \tag{25}$$

$$L_i \leq T^{Ar}_i \leq U_i \quad \forall i \in V'' \tag{26}$$

$$\begin{aligned} T^{Ar}_j \geq T^{Le}_i + T^{Tr}_{ij} \\ \forall i \in V''|v_{N+1}, \forall j \in V''|v_0, i \neq j \end{aligned} \tag{27}$$

$$T^{Le}_i = \begin{cases} T^{Ar}_i + T^{Se}_i, & \forall i \in V''|F \\ T^{Ar}_i + T^W_i + T^{Ch}_{i,n}, & \forall i \in F \end{cases} \tag{28}$$

The charging process in the depot is subject to constraints (16)-(18). Constraints (16) and (17) define the amount of energy that must be charged before departing the depot. According to constraint (18), each CEV must be charged with at least a certain amount of energy. Constraints (19) and (20) determine the amount of energy left at each node. CEV battery capacity in each station is ensured by constraint (21). Constraints (22) and (23) ensure that each customer is assigned only once and that outgoing arcs match incoming arcs at each node. Each customer's load capacity is determined by constraints (24) and (25). The time allowance for each customer is determined by constraints (26)-(28).

III. PROPOSED STRATEGY

Managing the charging of a fleet of CEVs at a depot with limited charging stations can be achieved by scheduling their charging times based on the operational conditions of the vehicles. This paper focuses on CEVs utilized in urban freight and delivery services, including those managed by prominent companies such as UPS, DHL, JD, Walmart

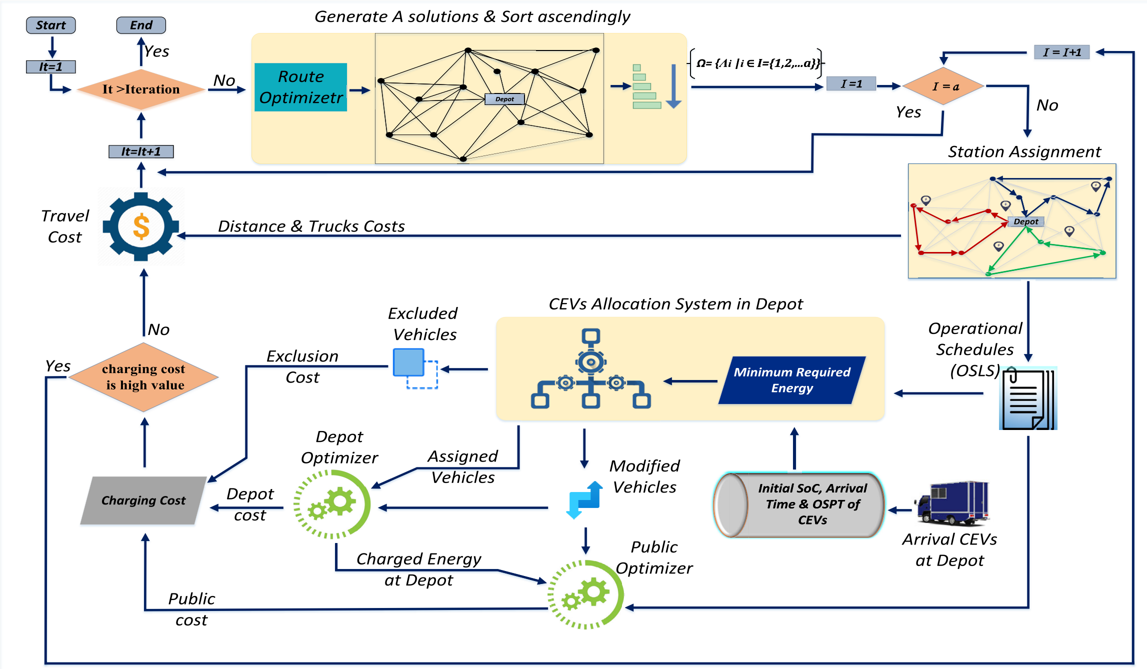

FIGURE 2. Flowchart of the proposed optimization strategy.

Inc, and FedEx. These CEVs adhere to strict operational timetables crucial for providing delivery services to clients. Furthermore, the demand for these CEVs is presumed to be consistent and fixed within the study's framework. However, our strategy is designed to accommodate minor variations, such as slight delays in CEV departure or arrival times, or minor fluctuations in demand, ensuring that the system can adapt within defined tolerance levels. The strategy adjusts for slight variations by considering a tolerance factor within each customer's scheduled time windows, enabling flexibility in service delivery without significant disruption.

Since the charging costs at depots are directly related to energy consumption and demand charges, it is imperative to optimize the charging time and power to avoid a significant increase in peak demand. In light of the limited number of depot stations and strict OSPT, it may be necessary to schedule the CEV charging at public charging stations in order to ensure the flow of logistic services. Considering the lack of public charging stations, it is necessary to optimize the routes for CEVs in order to facilitate public charging and reduce the total travel cost.

In order to address the aforementioned requirements, the strategy depicted in Fig. 2 is proposed. The proposed strategy utilizes a hierarchical approach to solve the routing and charging problems optimally in order to avoid local optimal solutions and high computational time incurred by individual-based metaheuristic algorithms [10], [28]. In this section, we begin by providing the overall process of the proposed strategy. Following this, the main components of the proposed strategy, including: the generation of operational schedules, the depot allocation system, the depot optimizer, and the public optimizer, are described in detail.

A. PROCESS OF PROPOSED STRATEGY

As shown in the flowchart, the proposed strategy is initialized by solving the routing problem using Ant Colony Optimizer (ACO) to identify the initial solutions of feasible routes. ACO is a probabilistic technique inspired by the natural foraging behavior of ants, designed to solve computational problems. It enhances optimization paths by mimicking the pheromone trails left by ants during their movement. This method entails artificial ants depositing pheromones based on solution quality, utilizing pheromone evaporation and heuristic information to guide decision-making. Widely applied in network routing, scheduling, and combinatorial optimization, ACO is praised for its adaptability and effectiveness in handling complex scenarios, though it requires meticulous parameter tuning and significant computational resources. Its proficiency in generating viable routes for the Electric Vehicle Routing Problem has been underscored in various studies, as demonstrated in references [10], [49].

The initial solutions are used to generate the OSLS of CEVs included in the solution. Each CEV's OSLS includes vehicle details (battery capacity, energy consumption), details about the customer being serviced (location, time window), details about the selected route (customer order, distance), and details about public stations (location, power capacity, waiting time).

Once the OSLS of CEVs are defined, the allocation system is used to assign the CEVs to the depot charging stations. CEVs arriving at the depot may be assigned to the charging stations with full or partial charging requirements, or excluded from the charging process, depending on station allocation status and charging demands of CEVs. After assigning CEVs, the depot optimizer is used to optimize the CEVs charging at the depot charging stations. Considering that CEVs assigned and charged partially at the depot should be charged during their driving cycle, the proposed strategy utilizes a public optimizer in order to schedule the charging of the CEVs at public charging stations.

As the charging costs at the depot and public stations are determined, the proposed strategy calculates the overall logistics cost by adding the distance cost of the route selected, the cost of used vehicles, and the cost of excluded customers as indicated in (15). A new population of feasible route solutions is then generated once the local and global pheromones of ACO have been updated by the best-fit solution at the beginning of the process. ACO runs several iterations before reaching the global best solution, which is found to be the route with the lowest overall cost.

B. OPERATIONAL SCHEDULES GENERATION

In the proposed strategy, OSLS are generated by using the ACO algorithm to solve routing problems, which has been used in a number of works, such as [10] and [49]. During each iteration, the ACO generates a population of feasible solutions $\Omega = \{\Lambda_1, \Lambda_2, .., \Lambda_a\}$ that satisfy all customers' loading and time window requirements. In Ω, solutions are arranged in ascending order according to their distance, where each solution may contain a single route or multiple routes. Let $\Phi_\Lambda = \{\varphi_1, \varphi_2, .., \varphi_K\}$ denotes the set of routes included in solution $\Lambda \in \Omega$. Each route in Φ_Λ is assigned one CEV, therefore the set of vehicles included in solution Λ is W_Λ.

The routing problem in the proposed strategy focuses on determining which routes would provide sufficient public charging stations while reducing the distance traveled. Therefore, the solution $\Lambda_1 \in \Omega$ with the shortest distance is selected, and the charging requirements of CEVs included in this solution are examined. Each route $\varphi \in \Phi_{\Lambda_1}$ should be assigned the public charging stations available between its nodes. Since there may be more than one station along the path between any two nodes, the station assignments are generally determined by their proximity to both nodes. Accordingly, the public station with the least increase in distance between the two nodes is assigned; provided that only one station is visited between any two nodes.

In our research, we adopt the M/M/k/R queuing model to predict waiting times at public charging stations, a methodology built upon defined operational assumptions. This model operates under a stochastic setting where arrivals and service times follow exponential distributions. Here, k represents the number of service channels (charging points) while R indicates the overall system capacity, including both the service channels and any available waiting spaces. The selection of this model is guided by its proven effectiveness and successful applications in related studies, as cited in references [52] and [53], illustrating its reliability in efficiently managing the dynamics of charging station utilization and customer wait times.

Following the assignment of public stations, the OSLS for each CEV in W_{Λ_1} will be generated. The operational schedules of CEVs in W_{Λ_1} is used by depot and public optimizers to optimize the charging process of CEVs. In the event that CEV charging at public or depot stations cannot be scheduled due to constraints breaches in operational schedules, the route is considered infeasible. Here, the OSLS is regenerated considering the route $\Lambda_2 \in \Omega$, and this process continues until CEV charging at depots and public facilities is scheduled.

C. CEV ALLOCATION SYSTEM AT THE DEPOT

Most studies in the literature assume that parking lots and depots have sufficient charging stations for parked vehicles. In spite of this, due to the increased adoption of CEVs and the power limitations of depots, charging stations may share more than one CEV during charging times. In view of the fact that CEVs have different levels of charging requirements (parking times and charging demands), they should be assigned to the charging station appropriately in order to meet their charging requirements. Accordingly, an allocation system is designed to decide the appropriate charging station and the order in which the CEVs will be assigned for charging, as shown in Algorithm 1.

In the allocation system, the required charging demand ($E^{req}_{D,n}$) and the minimum charging demand ($E^{min}_{D,n}$) of each CEV on arrival at the depot are determined by its OSLS. A CEV's minimum charging demand represents the minimum energy that is required to be charged at the depot, provided that the remaining energy can be charged at public charging stations found along the chosen route. As illustrated in Algorithm 1, the allocation system begins assigning the arriving *nth* CEV to the appropriate charging station based on its $E^{req}_{D,n}$. In the allocation process, the minimum time required to satisfy the charging demand is determined based on the full power rate of the depot station. Starting charging time of the arrival CEV at the station is determined by the ending charging time of the previous CEV in the queue. Therefore, the waiting time of the arrival CEV at each station is defined as the sum of charging times of all CEVs assigned at that station.

When the waiting times at depot charging stations exceed the parking time of an arrival CEV, the allocation system considers rearranging the CEVs assigned at the stations in order to ensure that the arrival CEV can be properly assigned. In the event that the arrival CEV cannot be assigned with $E^{req}_{D,n}$, the allocation system considers the $E^{min}_{D,n}$ of the arrival *nth* CEV and repeats the allocation process. CEVs assigned with minimal charging demands are included in $\overline{\overline{W}}$, which indicates the CEVs that are assigned and charged partially

Algorithm 1 CEV Allocation System at Depot Stations

Input: S, W_A, $E^{req}_{D,n}$, OSLS.
Output: AS, $\overline{W}$, $\overline{\overline{W}}$

Set stations' assigned time (AT_S) $\leftarrow 0$.
Set CEVs' charging time (Ch_n) $\leftarrow 0$
for $n \in W_A$ **do**
  Initialize Selected Stations $\leftarrow 0$
  Calculate Ch_n based on $E^{req}_{D,n}$ and P_{max}
  Calculate $E^{min}_{D,n}$.
  if Stations status not busy **then**
    Assign CEV to a station and Update status.
    Update $AT_S \leftarrow AT_S + Ch_n$ for the station.
  else
    while CEV is not assigned or excluded **do**
      Select a station to assign the nth CEV to its queue or between its allocated CEVs
      Selected Stations $\leftarrow$ Selected Stations+1.
      if $AT_S + Ch_n < t^{DP}_n$ **then**
        Assign the CEV to the station.
        Update $AT_S \leftarrow AT_S + Ch_n$ for the station.
      else
        if Selected Stations = $|S|$ **then**
          if CEV not in $\overline{\overline{W}}$ **then**
            Initialize Selected Stations $\leftarrow 0$
            Calculate Ch_n based on $E^{min}_{D,n}$, P_{max}
            Add the nth CEV $\leftarrow \overline{\overline{W}}$
          else
            if Allocated CEVs in $\overline{\overline{W}}$ **then**
              Add the nth CEV $\leftarrow \overline{W}$
            end if
            Initialize Selected Stations $\leftarrow 0$
            Reduce changing times of allocated CEVs at stations and include in $\overline{\overline{W}}$.
          end if
        end if
      end if
    end while
  end if
end for
Updated Information of AS, $\overline{W}$, $\overline{\overline{W}}$

at the depot stations. In some cases, the allocation system may be unable to assign arrival CEVs even with the minimum charging demand, due to the lack of public charging stations along the driving cycle and high charging demand. Due to this, the allocation system adds the arrival CEV to the list of excluded vehicles $\overline{W}$.

Once all arrival CEVs are assigned to charging stations, the allocation system generates AS, $\overline{\overline{W}}$, and $\overline{W}$ at the depot. AS identifies the order in which CEVs are assigned at each station and their charging requirements. This information is used in the next steps of the proposed strategy, as described in the following section.

Algorithm 2 Depot Charging Algorithm

Input: The population Size, Iteration Number, AS, OSPT
Output: C_D, t^{Start}_n, t^{End}_n, $P^{De}_{n,t}$, $\forall t \in \mathcal{T}$ & $\forall n \in W_A$

Set α, β, δ, and fitness values of GWO
Define the parking interval of each CEV.
Initialize charging period ($[t^{Start}_n, t^{End}_n]$) $\forall n \in W_A$ based on AS and parking interval.
while Iteration number not met **do**
  for Wolf in population Size **do**
    if CEVs have OSPT **then**
      Divide charging periods into $[t^{Start}_n, t^{Operate}_n]$, $[t^{Finish}_n, \bar{t}^{End}_n]$
      if $\bar{t}^{End}_n > t^{DP}_n$ **then**
        $\bar{t}^{End}_n \leftarrow t^{DP}_n$
        Add the nth CEV $\leftarrow \overline{\overline{W}}$
      end if
      Calculate AS_1 based on AS, $[t^{Start}_n, t^{Operate}_n]$
      Call Algorithm 1 to calculate AS_2 based on $[t^{Finish}_n, \bar{t}^{End}_n]$
    end if
    Define $\mathcal{AI}_{n,t}$ for each CEVs.
    Using Cplex to solve the optimization problem for $P^{De}_{n,t}$, $\forall t \in \mathcal{T}$ & $\forall n \in W_A$
    Calculate C_D based of $P^{De}_{n,t}$ $\forall t \in \mathcal{T}$ & $\forall n \in W_A$
    if C_D is assigned high values **then**
      Return zeros for t^{Start}_n, t^{End}_n $\forall n \in W_A$.
    else
      Update α, β,δ
      Update $[t^{Start}_n, t^{End}_n]$ $\forall n \in W_A$.
      Check the limits of $[t^{Start}_n, t^{End}_n]$ based on AS and parking interval.
    end if
  end for
end while
Update C_D, t^{Start}_n, t^{End}_n, $P^{De}_{n,t}$, $\forall t \in \mathcal{T}$ & $\forall n \in W_A$

D. DEPOT CHARGING OPTIMIZATION

Following the generation of AS for depot charging stations, the depot charging problem for CEVs is solved with the aim of reducing the charging cost of these vehicles. Considering that charging costs at depots are dependent on energy and demand rates, as indicated in (7), optimizing the power rate of depot stations over the charging periods of CEVs can provide the optimal minimization of charging costs. As the starting charging time for CEVs impacts their available charging periods, the optimal scheduling of the t^{Start}_n for CEVs is a key factor in optimizing the power rate of depot stations. Based on these requirements, the depot optimizer shown in Algorithm 2 is designed to optimize both the starting charging time for CEVs and the power rate of depot stations in a hierarchical manner. In the depot optimizer, Grey Wolf Optimizer (GWO) algorithm and the Cplex solver are used, which have been successfully applied in many studies [54], [55].

Algorithm 3 Public Charging Algorithm

Input: OSLS, F, $\overline{\overline{W}}$, E_n^D, $E_{D,n}^{req}$.
Output: C_P, $T_{i,n}^{Ch}$ $\forall i \in F$ & $\forall n \in W$

```
Set fitness value, Charging schedules, Γ
for n ∈ W̿ do
    Initialize C_P ← 0
    Define φ_n ∈ Φ_Λ and assigned public stations (F_n).
    Calculate the energy required to be charged at F_n based
    on E_n^D, E_{D,n}^{req}.
    Calculate T_{i,n}^{min}, T_{i,n}^{max} based on OSLS at each station
    i ∈ F_n.
    Define Γ based on T_{i,n}^{min}, T_{i,n}^{max}, ∀i ∈ F_n.
    for (charging schedule in Γ ) do
        for i ∈ F_n do
            Define detour distance to the station
            Update T_{i,n}^{min}, T_{i,n}^{max} based on charging times at
            previous stations along φ_n & detour distance
            if T_{i,n}^{min} > T_{i,n}^{max} then
                T_{i,n}^{Ch} ← 0
            else
                Update T_{i,n}^{Ch} based updated T_{i,n}^{min}, T_{i,n}^{max} &
                previous charging schedule.
            end if
            Update charging schedule in Γ based on T_{i,n}^{Ch}
        end for
    end for
    Calculate fitness values for charging schedules.
    Define charging schedule with lowest fitness value
    C_P ← C_P + min{Fitness values}
end for
return C_P, Optimum charging schedules of CEVs
```

The depot optimizer is initiated by using the GWO algorithm to generate the initial population of t_n^{Start} and t_n^{End}, $\forall n \in W_{\Lambda_1}$. In the GWO, the starting and ending times are determined based on the AS of depot stations, where the charging demand and order of CEVs remain unchanged. Following the determination of the charging times for CEVs, the charging period $\mathcal{AI}_{n,t}$ for each CEV is calculated in accordance with (2). When a CEV's OSPT overlaps with its calculated charge period, the depot optimizer divides the charging period into two periods as shown in (3). As a result, AS is divided into two allocation schedules (AS_1 and AS_2) in accordance with the charging periods in (3). AS_1 is defined by updating AS to include $t_n^{Operate}$ of OSPT, whilst AS_2 is defined by applying Algorithm 1 to CEVs returning to the stations from OSPT.

In the case where the AS_2 overlaps with the departure time of CEVs, the depot optimizer reduces the charging periods in AS_2 and compares the total charged energy with the $E_{D,n}^{min}$ of CEVs. When the total charged energy exceeds the $E_{D,n}^{min}$, the depot optimizer adds the CEV in $\overline{\overline{W}}$; otherwise, the CEV is included in $\overline{W}$. The depot optimizer uses the Cplex optimizer to solve optimally the depot charging problem and calculate the depot charging costs. After performing the previous steps for the maximum number of iterations, the depot optimizer chooses the optimal solution that has the lowest depot charging cost and the least number of CEVs included in $\overline{W}$.

E. PUBLIC CHARGING OPTIMIZATION

CEVs charging at public charging stations is necessary when energy charged at depot charging stations is not sufficient to meet their operational schedules. The CEVs that require charging at public stations have been included in $\overline{\overline{W}}$ throughout the previous steps of the proposed strategy. The charging of these CEVs at public stations should be optimized in order to reduce the costs associated with public charging. To this end, a heuristic algorithm is developed as a public optimizer to solve the public charging problem, which is shown in Algorithm 3. The heuristic algorithm is proposed as opposed to a metaheuristic algorithm to solve the public charging problem in order to reduce the computational load.

In the heuristic algorithm, the charging time limits defined by $[T_{i,n}^{min}, T_{i,n}^{max}]$ at each public station are determined by considering the logistical constraints of the CEV route without visiting the public stations. $T_{i,n}^{max}$ is the minimum difference between the arrival time and the upper limit of time window ($L_i - T_i^{Arr}$) of all nodes located after the station i along the route. $T_{i,n}^{min}$ is dependent on the amount of energy required for the CEV to reach the nearest station from station i. Whenever CEV charging is scheduled across public stations, the search space limits are updated accordingly. $T_{i,n}^{max}$ is updated by taking into account the time it takes to fully charge the CEV, as well as the time elapsed at previous charging stations. $T_{i,n}^{min}$ is updated in accordance with the CEV's energy levels when it reaches the station.

Updated $T_{i,n}^{min}$ and $T_{i,n}^{max}$ are used to optimize public charging of CEVs at each public charging station. On the basis of these limits, the heuristic algorithm generates the possible combinations of charging schedules (Γ) for CEVs at public stations along their route. Afterwards, the optimizer calculates the public charging costs for each charging schedule in Γ, returning the solution with the lowest cost among all charging schedules.

IV. RESULTS AND PERFORMANCE ANALYSES

Two OSPT scenarios for CEVs and three case studies are simulated to evaluate the performance of the proposed strategy. In the case studies, the number of customers served and public charging stations are different. Case 1 involves the service of 15 customers and the availability of 4 public stations. Five public stations and 21 customers are considered in case 2. In case 3, there are 50 customers and 8 public stations. During these case studies, two different scenarios of OSPT for CEVs are investigated. Scenario-I assumes that the CEVs will be parked until they depart. Scenario-II involves the CEVs leaving for a specific period of time

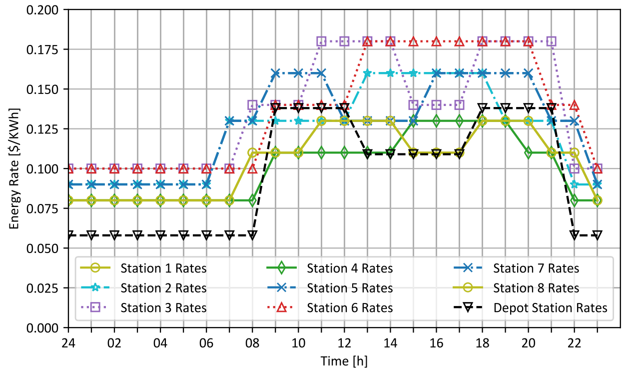

FIGURE 3. TOU energy tariffs of public and depot stations for a day.

before returning to charging stations. In Scenario-II, CEVs are dispatched uniformly between 22:00 and 1:00 for OSPT, while OPST lasts between 1.5 and 2.5 hours.

Case studies are based on benchmark instances that are investigated in works [12], [47], [49], and [56]. A number of parameters are extracted from these benchmark instances, including customer and station locations, time windows, service times, loading capacities, etc. Each of the CEVs in the depot has a battery capacity of 150 kW, a load capacity of 200 kg, an average speed of 60 km/h.

The optimization of charging schedules and overall efficiency in CEVs is heavily influenced by fuel consumption, quantified by energy consumption per kilometer. This metric is determined through tests conducted under various conditions or simulations that consider variables such as vehicle dynamics and the efficacy of the electric drivetrain system. Optimizing vehicle design, routing, and operational strategies significantly affects energy consumption rates that can lead to considerable savings [57], [58]. This paper uses a benchmark figure of 0.9 kW/km for fuel consumption. In addition, this paper considers eight public charging stations with power rates of $P = [25, 40, 50, 25, 40, 50, 40, 25]$ kW, and TOU energy pricing tariffs shown in Fig. 3 [51], [59].

At the depot, there are only three charging stations with a 19.2 kW charging rate. ToU energy tariffs for charging at the depot, shown in Fig. 3 follow industrial electricity tariffs proposed in [59] and [60]. A demand cost of $8/kW is also included in industrial electricity tariffs. The base-load profile for a commercial facility is based on the average load profile of the LGS sector in the service area of South California Edison [61]. CEVs from the previous shift arrived primarily between 16:30 and 18:00 according to [62]. The initial SoC at depots has also been uniformly distributed between 0.2 and 0.4.

A. SIMULATION IMPLEMENTATION

We conduct our simulation using Python 3.7 on a desktop computer equipped with an Intel Core i7 processor, operating at 3.19 GHz. Throughout the simulation, which spans a predefined period, we implement optimization techniques iteratively. Initially, we utilize ACO to devise feasible routes that meet logistical requirements prior to the implementation of charging strategies. The simulation schedules the arrival of CEVs at depots based on their designated arrival times and adjusts queuing based on the available data for public charging stations.

We simulate charging strategies using GWO and Cplex. GWO determines the optimal start and end times for charging each vehicle, and the simulation runs for a 24-hour period to accommodate the integration of Cplex. This integration allows Cplex to optimize the charging schedules of each CEV at 15-minute intervals, enabling adjustments during parking and potentially facilitating the use of V2V charging technologies.

To mitigate computational demands, we employ a heuristic algorithm for scheduling CEV charging at public stations. After establishing optimal charging schedules for a feasible route, the ACO algorithm generates a new route, and the simulation proceeds until all iterations are complete.

For continuous CEV operation, the simulation calculates the SoC at each node to ensure there is sufficient battery energy for reaching the next charging station. Routes are deemed infeasible if the SoC is insufficient. SoC calculation involves determining the remaining energy at each node using (20), which factors in distance, fuel consumption, and energy previously charged energy. Subsequently, SoC at each node is computed by dividing the remaining energy by the CEV's energy capacity.

B. SIMULATION RESULTS

A summary of the simulation results for the case studies under Scenario-I and Scenario-II is presented in Table 1 and Table 2. These results can be interpreted as follows.

1) CASE 1: RESULTS AND OBSERVATIONS

In case 1, the number of vehicles used for logistics is lower than the number of charging stations available at the depot. Thus, the charging period of each vehicle depends solely on its availability as indicated in (2) and (3). Using the proposed strategy, the charging profile of CEVs at depot stations is coordinated over charging periods to achieve the lowest depot costs. It is noteworthy that the depot cost in Scenario-II is higher than in Scenario-I due to the OSPT for CEVs, which reduces the charging periods of CEVs during the lower energy tariff intervals. Furthermore, it can be observed in both scenarios that CEVs travel the same routes and charge at the same public stations. The reason is despite the increase in depot costs in Scenario-II, the total travel cost of this path is still lower than other feasible travel paths. In the proposed strategy, the travel paths are optimized to accomplish the minimum travel cost specified in (15) while ensuring the continuity of CEVs before returning to the depot. For illustration, let us consider Fig. 4, which illustrates the optimal routes of the CEVs in Case 1.

Figures 5 and 6 illustrate the SoC of the two CEVs at each node along their respective routes. According to Fig. 5,

TABLE 1. Optimization results for cases studies under scenario-I.

Case Study	|W|	Veh. No.	Cos. No.	$E^{req}_{D,n}$	Depot Charging: Station No.	Depot Charging: t^{Start}_n	Depot Charging: E^D_n	Public Charging: Station No.	Public Charging: T^{Ch}_i	Public Charging: $E^P_{i,n}$	Travel Cost: C_D (\$)	Travel Cost: C_P (\$)	Travel Cost: C_T (\$)
Case 1	2	1	5	144.6	s_1	16.5	144.6	-	-	-	11.4	19.5	390.5
		2	5	204.2	s_2	16.6	150	f_2	1.64	65.5			
Case 2	4	1	8	198.4	s_1	17.7	150	f_1	2.29	57.2	22.6	21	707.4
		2	4	132	s_2	17.8	132	-	-	-			
		3	5	169.8	s_3	18	150	f_2	0.59	23.5			
		4	4	145.3	s_1	2.1	145.3	-	-	-			
Case 3	8	1	10	160.1	s_1	16.6	83.6	f_3	1.6	80.1	47.2	23.5	1206.3
		2	5	137.4	s_2	17.1	127.4	-	-	-			
		3	6	117.7	s_3	17.2	117.7	-	-	-			
		4	7	144.2	s_3	0.23	144.2	-	-	-			
		5	5	125.4	s_2	22.2	125.4	-	-	-			
		6	7	144.2	s_1	20.6	144.2	-	-	-			
		7	6	133.3	s_2	2.8	133.3	-	-	-			
		8	4	156.3	s_1	2.6	103.9	$[f_4, f_7]$	[0.95, 0.87]	[23.7, 34.6]			

TABLE 2. Optimization results for cases studies under scenario-II.

Case Study	|W|	Veh. No.	Cos. No.	$E^{req}_{D,n}$	Depot Charging: Station No.	Depot Charging: t^{Start}_n	Depot Charging: E^D_n	Public Charging: Station No.	Public Charging: T^{Ch}_i	Public Charging: $E^P_{i,n}$	Travel Cost: C_D (\$)	Travel Cost: C_P (\$)	Travel Cost: C_T (\$)
Case 1	2	1	5	144.6	s_1	16.5	144.6	-	-	-	19.1	19.5	399.5
		2	5	204.2	s_2	16.6	150	f_2	1.64	65.5			
Case 2	4	1	8	198.4	$[s_1, s_1]$	[17.7, 5.7]	150	f_1	2.29	57.2	27.7	21	712.4
		2	4	132	$[s_2, s_2]$	[17.8, 1.6]	132	-	-	-			
		3	5	169.8	$[s_3, s_3]$	[18, 2.4]	150	f_2	0.59	23.5			
		4	4	145.3	$[s_1, s_1]$	[1.9, 4.1]	145.3	-	-	-			
Case 3	8	1	10	174.5	$[s_1, s_1]$	[16.6, 0.9]	150	f_8	1.2	29.3	54.2	16.9	1234.1
		2	8	139.4	s_2	17.1	139.4	-	-	-			
		3	8	164.2	$[s_3, s_3]$	[17.2, 0.8]	150	f_7	0.5	21.2			
		4	6	167.5	$[s_2, s_2]$	[21.4, 1.7]	150	f_7	0.8	32.9			
		5	7	146.4	$[s_3, s_1]$	[22.9, 2.4]	146.4	-	-	-			
		6	3	105.4	s_3	5.3	105.4	-	-	-			
		7	4	130.4	$[s_1, s_3]$	[22, 4.5]	124.4	f_2	0.24	9.8			
		8	4	112.1	$[s_2, s_2]$	[23.3, 6]	106.9	f_8	0.25	6.5			

charging CEV 1 at the depot is adequate to serve all customers and return to the depot. Conversely, Fig. 6 illustrates that to ensure the continuous operation of CEV 2 along its route, a visit to station f_2 is necessary. A short detour distance and low TOU tariffs led to f_2 being selected over other stations along the route. The proposed strategy schedules the visit to f_2 station before returning back to the depot to avoid disrupting logistics services. The SoC of CEVs at depot arrival in this simulation is set to be greater than 0.15.

2) CASE 2: RESULTS AND OBSERVATIONS

In case 2, there are more vehicles used for logistics than charging spots at the depot. Consequently, the *AS* assigns CEVs to depot stations based on their charging requirements and arrival times. According to Table 1 for Scenario-I, CEVs 1 and 4 are assigned to station s_1, with CEV 4 being assigned after CEV 1. *AS* of CEVs for Case 2 under Scenario-I is shown in Fig. 7. It can be observed from the figure that the charging periods for CEV 2 and CEV 3 are dependent on their availability times denoted in (2).

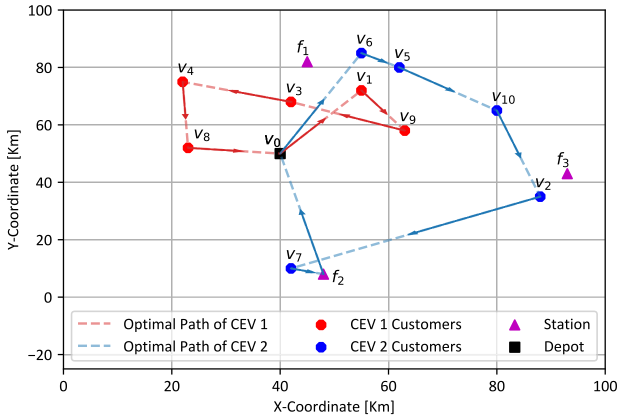

FIGURE 4. Optimal routes for CEV 1 and 2 under Case 1.

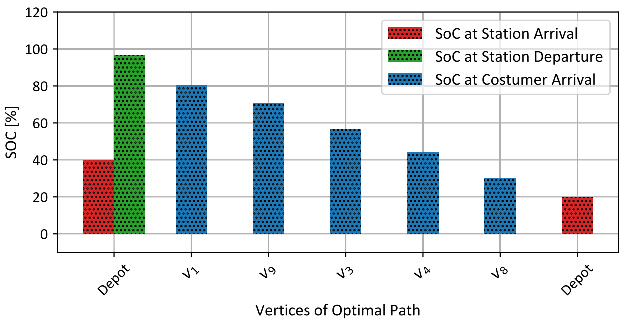

FIGURE 5. SoC at each node of CEV 1's route under Case 1.

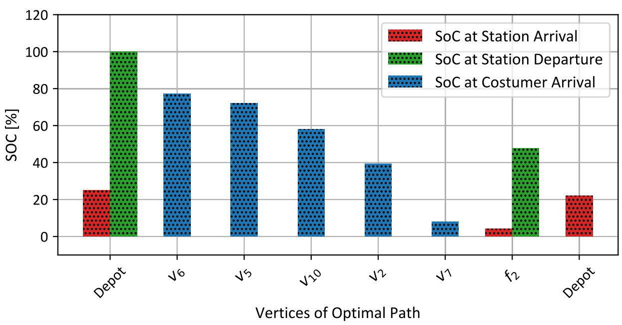

FIGURE 6. SoC at each node of CEV 2's route under Case 1.

For vehicles that share the same charging station, CEV 1's charging period is set longer than that of CEV 4 based on the availability of the vehicles and the requirement to maintain a minimum depot charging cost. This is illustrated in Fig. 8, which shows the SoCs of CEVs at depot stations. As can be seen in the figure, increasing charging period of CEV 1 allows the charging rate of s_1 to be regulated between 18:00 and 21:00 in order to avoid an increase in the depot cost due to energy and demand tariffs. As soon as the charging period for CEV 1 ends, CEV 4 continues to charge at the maximum rate in station s_1 until the required energy is achieved.

Similarly to Scenario-I, CEVs 1 and 4 are assigned to station s_1 in Scenario-II, with CEV 4 assigned after CEV 1. Since CEVs undergo OSPT, the *AS* of CEVs are divided into (AS_1, AS_2), which represent the periods before and after the OSPT. *AS* of CEVs for Case 2 under Scenario-II are

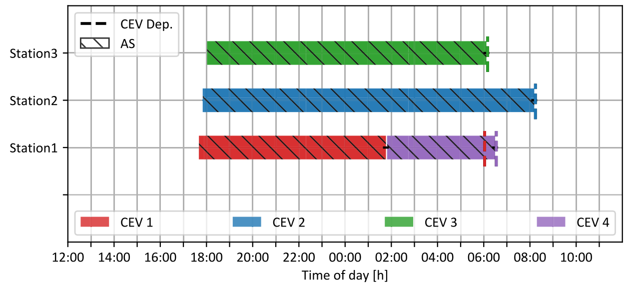

FIGURE 7. *AS* of CEVs at depot stations for Case 2 under Scenario-I.

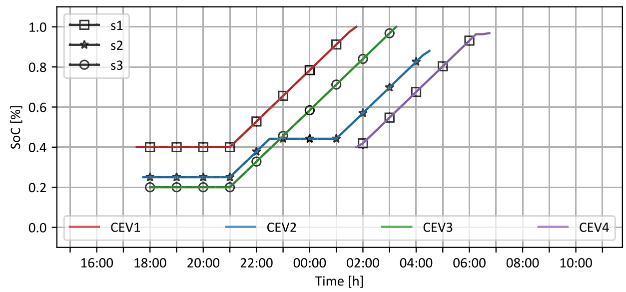

FIGURE 8. SoC of CEVs at depot stations for Case 2 under Scenario-I.

shown in Fig. 9. It can be seen that CEV 4 is allocated before CEV 1 during AS_2, because CEV 4 returns from OSPT before CEV 1. Although the OSPT reduces the charging periods for CEVs when compared to Scenario-I, the proposed strategy optimizes the two charging periods of each CEV to minimize the depot charging cost as possible. Fig. 10 shows the SoCs of CEVs at depot stations for Case 2 under Scenario-II. This figure shows how the proposed strategy optimizes the charging profile of CEV 2 and CEV 3 between 18:00 and 21:00 in order to reduce depot charging costs. Due to the OSPT, the charging periods for CEV 1 and CEV 4 are sufficient to charge the required energy before departure. Accordingly, the depot charging cost increases slightly compared to Scenario-I. CEVs' travel paths or public charging schedules are not affected by this increase in depot costs as shown in Table 2.

3) CASE 3: RESULTS AND OBSERVATIONS

For case 3, there are eight CEVs that are used for logistical services. These CEVs have different charging requirements that need to be met in accordance with their operational schedules. The proposed strategy assigns CEVs to depot charging stations based on their full charging requirements. Whenever charging requirements cannot be assigned fully, the charging requirements are reduced and assigned as described in Algorithm 1.

Table 1 for Scenario-I shows that each of the stations s_2, and s_3 has three CEVs, and station s_1 has two CEVs. For CEV1, the charging requirement is greater than the CEV capacity, so it is necessary to visit a public charging station in order to fulfill its logistical services. Charge requirements for other CEVs are less than CEV capacity and can be charged at the depot. Due to the limited number of depot stations, however, the charging requirement for CEV 8 is reduced in

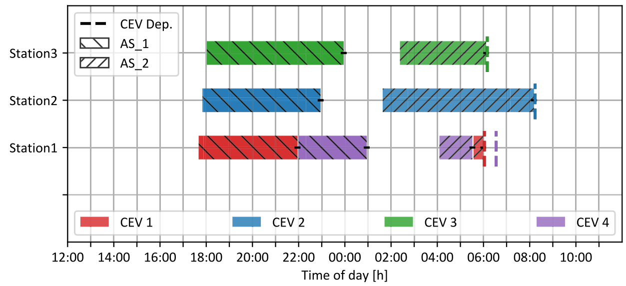

FIGURE 9. *AS* **of CEVs at depot stations for Case 2 under Scenario-II.**

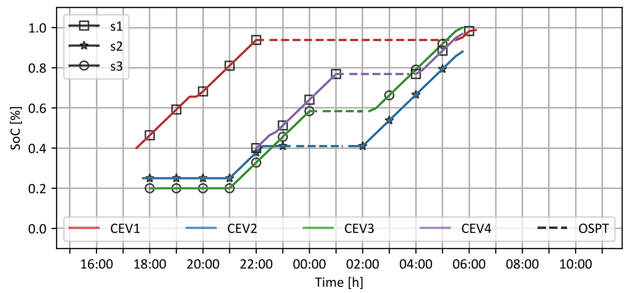

FIGURE 10. **SoC of CEVs at depot stations for Case 2 under Scenario-II.**

TABLE 3. **Comparison of existing/benchmark algorithm and proposed strategy for case studies 1-3.**

		Existing/Benchmark*			Proposed		
Case Study	Scenario	C_T (\$)	C_D (\$)	$\lvert\overline{W}\rvert$	C_T (\$)	C_D (\$)	$\lvert\overline{W}\rvert$
Case 1	Scen-I	404.8	24.4	-	390.5	11.4	-
	Scen-II	404.8	24.4	-	399.5	19.1	-
Case 2	Scen-I	748.3	94.2	-	707.46	22.6	-
	Scen-II	748.3	94.2	-	712.4	27.7	-
Case 3	Scen-I	1467.2	115.7	1	1206.3	47.6	-
	Scen-II	1772.1	109.9	2	1234.1	54.2	-

*) The ACO Algorithm takes into consideration different variants studied in [10], [12], [49], [51].

TABLE 4. **Computational time comparison of existing/benchmark algorithm with proposed strategy for case 2 under Scenario-II.**

Algorithm	Case 1	Case 2	Case 3
Existing/Benchmark*	22.5 sec	29.8 sec	68.7 sec
Proposed Strategy	27.8 sec	40.7 sec	95.6 sec

*) The ACO Algorithm takes into consideration different variants studied in [10], [12], [49], [51].

order to assign it to s_3. Therefore, CEV 8 visits the public stations f_4 and f_7 so that continuity is maintained until it reaches the depot. When the CEV is charged at the public charging station, the energy used during the detour from the proposed route to the station should be compensated.

In Scenario-II, CEVs undergo OSPT, which reduces the charging period, thereby reducing energy charged in the depot. When using the optimized travel routes of Scenario-I, some of these CEVs experience discontinuity during their driving cycles. Thus, the proposed strategy defines different travel paths to ensure the continuity of logistic services while minimizing total travel costs. Table 2 for Scenario-II shows that 8 CEVs are used for logistics services based on the new travel routes. According to the OSPT, these CEVs may be assigned to depot stations differently in AS_1 and AS_1. As an example, CEV 7 is assigned to s_3 in AS_1 and s_1 in AS_2. In addition, it should be noted that 5 CEVs require a visit to public charging stations during their driving cycle, as opposed to two CEVs in Scenario-II.

C. PERFORMANCE OF PROPOSED STRATEGY

According to the authors' knowledge, a number of routing and charging algorithms have been considered in the literature, but none have considered charging CEVs with a limited number of depot charging stations, including OSPT, TOU tariffs at depots and public charging stations, and depot demand charges. Because of this, it is not possible to directly compare the proposed models in the literature. For comparison purposes, the ACO algorithm was used to solve the charging problem, taking into consideration different variants studied in [10], [12], [49], and [51]. In this ACO algorithm (called the existing/benchmark algorithm in this paper), the CEV is assigned to the charging station in the depot according to its arrival time. Whenever the CEV starts charging, it continues to charge at the maximum charging rate until it reaches its required energy or leaves the depot. CEVs departing for OSPT return to the same charging station after OSPT. In addition, the existing/benchmark algorithm assigns only one public charging station to each path of the route. Table 3 lists the simulation results for comparison.

Under Cases 1 and 2, the proposed strategy has better results in terms of reducing the total cost significantly. The existing/benchmark algorithm responds to different scenarios similarly because the charging period for CEVs is only determined by its energy requirements, so there is no optimization for demand and energy costs. In the case of large customers, the proposed strategy performs better in terms of total cost and continuity of logistics service than the existing/benchmark algorithm. Under Scenario-II in Case 3, the proposed strategy can save up to 30% and ensures the continuity of all optimized CEVs, whereas the existing/benchmark algorithm loses the continuity of two CEVs. The reduction in costs is achieved through the optimization of demand charges and TOU tariffs, strategic assignment of CEVs to depot charging stations, and the implementation of an efficient routing algorithm. This strategy effectively reduces expenses, improves scalability, and ensures continuous service, even in situations with extensive customer demands and constrained charging infrastructure. According to these results, the proposed strategy can play a significant role in increasing the adoption of CEVs in the depot fleet without requiring infrastructure upgrades.

The proposed strategy has been simplified in terms of computational complexity by proposing a heuristic algorithm rather than a meta-heuristic algorithm for the public optimizer. In addition, the search spaces of GWO and ACO have

TABLE 5. Optimization results for case 3 under Scenario-II with different values of time windows and customers number.

Time Windows	$\lvert V\rvert$			$\lvert V\rvert + 10$		
	|W|	C_P ($)	C_T ($)	|W|	C_P ($)	C_T ($)
$\{[L_i, U_i]\}$	8	16.9	1234.1	9	32.6	1390.2
$\{[L_i+1, U_i-1]\}$	8	25.3	1270.2	10	20.2	1416.8
$\{[L_i-1, U_i+1]\}$	7	23.6	1155.9	8	23.2	1285.9

been reduced by updating the space limits and eliminating repeated solutions, respectively. In this way, the entire strategy was able to be computed in less time. Table 4 shows a comparison of the computational time of the proposed strategy and the existing/benchmark algorithm under different cases. Under Case 1, the proposed strategy displays a similar computational time to the existing/benchmark strategy. When the number of customers is increased like in Cases 2 and 3, the proposed strategy takes more time to converge than the existing/benchmark algorithm due to the need to allocate and optimize the CEV charging at the depot. This increase in computational time is offset by the reduction in the total cost and maintaining the logistics services, as shown in Table 3.

D. IMPACT OF PUBLIC CHARGING STATIONS AND TIME WINDOWS

The time windows of customers have a major impact on the feasibility of routes for CEVs and the possibility of charging CEVs at public charging stations. This impact is highlighted by the increasing number of customers being served and the lack of public stations. Consequently, the proposed strategy should be evaluated in light of time windows and the lack of public stations. To investigate this situation, the number of customers in Case 3 is increased from 50 to 60 while keeping the number of public stations the same. The proposed strategy is then evaluated under different time windows as shown in Table 5. Under the time windows of Case 3, an increase in customer numbers will result in an increase in CEVs to compensate for the lack of public stations. There is an increase in public charging of these CEVs due to the detour distance to the existing public stations. With the tight time window of one hour for the |V| customers, the proposed strategy considers different travel paths for CEVs to enable their charging at public stations, which increased the total cost of the logistics. The lack of public stations and tight time windows ultimately result in a further increase in CEV numbers for (|V|+10) customers in order to be able to charge in existing public stations and maintain logistics services. If customers' time windows are relaxed by 1 hour, shorter routes with enough public stations become available, resulting in fewer CEVs and a lower overall cost.

V. CONCLUSION

This paper proposed a strategy to optimize the routing and charging process for CEVs considering the limited charging infrastructure at the depot. As part of the proposed strategy, the allocation system is designed to assign arrival CEVs to depot stations appropriately. The proposed strategy used a combined algorithm of GWO and Cplex optimizers to manage the charging of assigned CEVs in accordance with demand charging and operational scheduling during parking periods. A heuristic algorithm was used to schedule CEVs charging at public stations along feasible routes of vehicles. In the proposed strategy, feasible routes are generated by ACO algorithm in order to minimize travel costs and ensure continuity of logistics services.

Through extensive simulation case studies, the effectiveness of the proposed strategy has been confirmed. Two OSPT scenarios without and with CEVs leaving for a specific period before returning to charging stations are simulated. For each scenario, three case studies involving the service of 15, 21, and 50 customers with the availability of 4, 5, and 8 public stations are investigated (Tables 1-2). Based on the simulation results, it can be concluded that the limited charging infrastructure at the depot has an impact on the charging schedules of CEVs and the routes of logistics services. Results showed that the proposed solution reduced the total travel cost by up to 30% and ensured continuum of logistics services, whereas the existing/benchmark algorithm caused some CEVs to lose continuity (Tables 3-4). In our future research, we aim to design a strategy capable of addressing dynamic operational schedules, unforeseen demand, and routing changes for CEVs, particularly in the context of a limited CEV Fleet. This strategy will enhance flexibility and resilience in urban logistics, ensuring adaptability to the unpredictable nature of delivery services. Furthermore, we intend to collaborate closely with logistics companies to obtain essential data for refining our strategy. Our objective is to implement this strategy in real-world scenarios to demonstrate its effectiveness and cost savings. Through this demonstration, we hope to validate the practical advantages of our approach and encourage widespread adoption among companies for managing their electric vehicle fleets.

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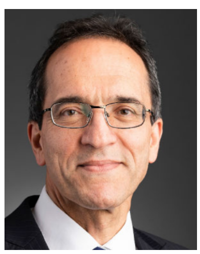

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