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OPTIMAL MIXED FLEET AND CHARGING INFRASTRUCTURE PLANNING TO ELECTRIFY DEMAND RESPONSIVE FEEDER SERVICES UNDER STOCHASTIC DEMAND

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1. INTRODUCTION

Electrification of mobility services has become increasingly popular motivated by CO2 emission reduction targets, in the pursuit to reduce to 55% below the 1990 level the greenhouse gas emissions by 2030 (IEA, 2022). Since the operational range of electric vehicles (EVs) is constrained by their battery capacity, the performance of EV-operated mobility services depends on the configuration of charging infrastructure (i.e., fast chargers in support of overnight slow chargers) (Macrina et al., 2019). This is especially true for Mobility on-demand services (MODs), such as demand-responsive feeder services (DRFS), where the spatiotemporal variability of demand impacts vehicle routing and hence energy consumption, making fleet planning and charging management a challenging problem. In the real-world transition to full electrification, it is realistic to assume mixed fleet operation with EVs and gasoline vehicles (GVs), due to operators' budget constraints (Goeke and Scheider, 2015). Ultimately, the level of electrification will be determined by the target CO2 emission reduction and the investment cost to achieve the target.

There is extensive literature focusing on joint fleet management and charging infrastructure planning for fixed-route buses (e.g., Gunschinsky et al. 2021). However, few studies have investigated the context of MODs where routing and scheduling problems embed more complexity. Ma and Xie (2021) proposed a joint optimization for fast charging station location and dynamic vehicle-charging assignment problem for electric MODs considering stochastic demand with fixed fleet size. Having assumed a fully electric fleet, their model cannot consider the mixed fleet as well as a CO2 emission reduction target. The mixed fleet green vehicle routing problem is often utilized to solve routing and scheduling problems for the mixed fleet with EVs and GVs with the consideration of environmental impact. However, most research assumes fixed charging infrastructure, with CO2 emissions minimized rather than being a target reduction level (Macrina et al., 2019). These approaches fail to reveal to what extent charging infrastructure configuration impacts upon service performance under different CO2 reduction targets.

To address the above issues, we develop a joint fleet size and charging infrastructure optimization method under stochastic customer demand given the configurable CO2 emission reduction target, charging station capacity constraints and partial recharge. An efficient solution algorithm is proposed and tested. Introducing CO2 emission target instead of minimizing CO2 emission will provide more flexibility for DRFS operators to manage their transition toward electric mobility.

2. METHODOLOGY

2.1 Problem description

We consider the joint fleet size and charging infrastructure planning problem for the electrification of DRFS currently operated with GVs in a rural area. We consider total electrification cost to include charging infrastructure investment costs, fleet acquisition costs of EVs and energy consumption costs to serve the demand, all converted into per diem costs. Customer demand is assumed stochastic following some probability distribution. Given a CO_2 emission reduction target, DRFS operator aims to minimize the service electrification cost while ensuring a consistent service level, despite the variability in daily customer demand. Several candidate locations are predetermined for building charging stations with fast chargers allowing quick recharging during the operation. To maximize the mixed fleet DRFS performance, the charging infrastructure configuration (i.e., location, number of chargers and their types) are jointly decided with the EV acquisition, while meeting constraints of the local power grid. The DRFS operates on a set of predefined flexible bus stops which densely cover the service area to assure all potential customers' origins/destinations are within reasonable walking distance. Customers submit their trip request specifying the pick-up/drop-off locations and arrival times. Destinations are either bus stops, or a train station where scheduled transit service is offered.

The considered problem is a bi-level optimization problem where the upper-level problem (UP) determines the number of charging stations and chargers installed at each charging station whereas the lower-level problem (LP) minimizes the total routing and EV acquisition costs of the mixed fleet under the constraints of CO_2 emission reduction target and charging station capacity, informed by the upper-level decision. The UP minimizes the daily equivalent of the total expenditure to install the charging infrastructure (e.g., construction costs, costs of transformers, installation costs) and the expected total costs of the fleet acquisition (for EV), maintenance, and operational (energy consumption) cost assuming the stochastic customer demand. The maximum number of chargers installed at each station is constrained by the local grid capacity. Given a charging infrastructure configuration and a set of customer requests, the LP is formulated as a mixed fleet electric dial-a-ride problem (Bongiovanni et al., 2019; Hiermann et al., 2019) with vehicle capacity, time windows and charging station capacity constraints and partial recharge. The hard time windows are associated at transit stations to ensure acceptable transfer times for customers to the scheduled transit services. All customers need to be served within a maximum ride time, defined as the direct trip multiplied by a detour factor. As the LP is a variant of electric vehicle routing problem with capacitated charging station, it is difficult to solve (Lam et al., 2022). For the sake of brevity, we omit the full formulation of the bi-level problem in this short paper. The CO_2 emission constraint is of particular interest for this study and is formulated as follows.

$$\sum_{k \in K} \sum_{(i,j) \in A} \theta^k \beta^k c_{ij} x_{ij}^k \leq (1-\pi)\Gamma(\xi) \tag{1}$$

where x_{ij}^k is the decision variable indicating if arc (i,j) is travelled by vehicle k. β^k is the energy consumption rate for vehicle k. θ^k is the CO_2 emission rate per energy consumption of vehicle k. c_{ij} is the travel distance from vertex i to vertex j. π is the targeted user-defined CO_2 emission reduction rate with respect to the maximum CO_2 emission to serve demand scenario ξ , $\Gamma(\xi)$, with GVs only.

2.2 Solution algorithm

The considered bi-level optimization problem is NP-hard as the LP is a variant of the mixed fleet dial-a-ride problem. To handle the stochastic demand, we propose a deterministic annealing (DA) based metaheuristic (Braekers et al., 2014) to solve LP efficiently using dedicated local search operators to minimize the fleet size. To incorporate CO_2 emission constraint, a penalty function approach is adopted when the CO2 emission of a tentative solution exceeds the threshold. The sub-problem of charging scheduling under capacitated charging stations and partial recharge is solved efficiently by adopting a mixture of random and greedy charging operation scheduling strategy. As we assume the stochastic demand, maximum amount of CO_2 emission from total routing distance varies to each demand scenario. Hence, given a charging infrastructure configuration solved in UP, a LP is solved twice for each demand scenario, once with only GVs to obtain the maximum CO_2 emission and then with a mixed fleet.

The UP is solved by exploring the charging infrastructure configuration based on the number of chargers starting from the smallest value. Given the number of chargers, the different allocations of chargers at the charging station will be exhaustively tested (e.g., if there are two charging stations, the allocation of two chargers can be (2,0), (1,1), and (0,2)). For each charging infrastructure configuration, the LP is solved for multiple demand scenarios from which the expected DRFS electrification cost is estimated. Then, the minimum expected electrification cost among different charging configurations given the number of chargers is compared with the one with the greater number of chargers. If the minimum expected electrification cost decreases by increasing the number of chargers, the simulation is extended to the greater number of chargers. Otherwise, the simulation is terminated with the current number of chargers. In this way, we can get the best solution without exploring all possible permutations. The electrification cost is further compared among different allocations of chargers at the charging stations. The solution with the lowest total electrification cost among them is determined as the optimal solution.

Once the charging infrastructure is optimized, the fleet composition will be determined. To balance the fleet acquisition cost and customer satisfaction, we consider a robust scenario where the fleet size is determined to satisfy uncertain customer demand by at least a given percentage for all demand scenarios. The solution framework can be referred in Figure 1.

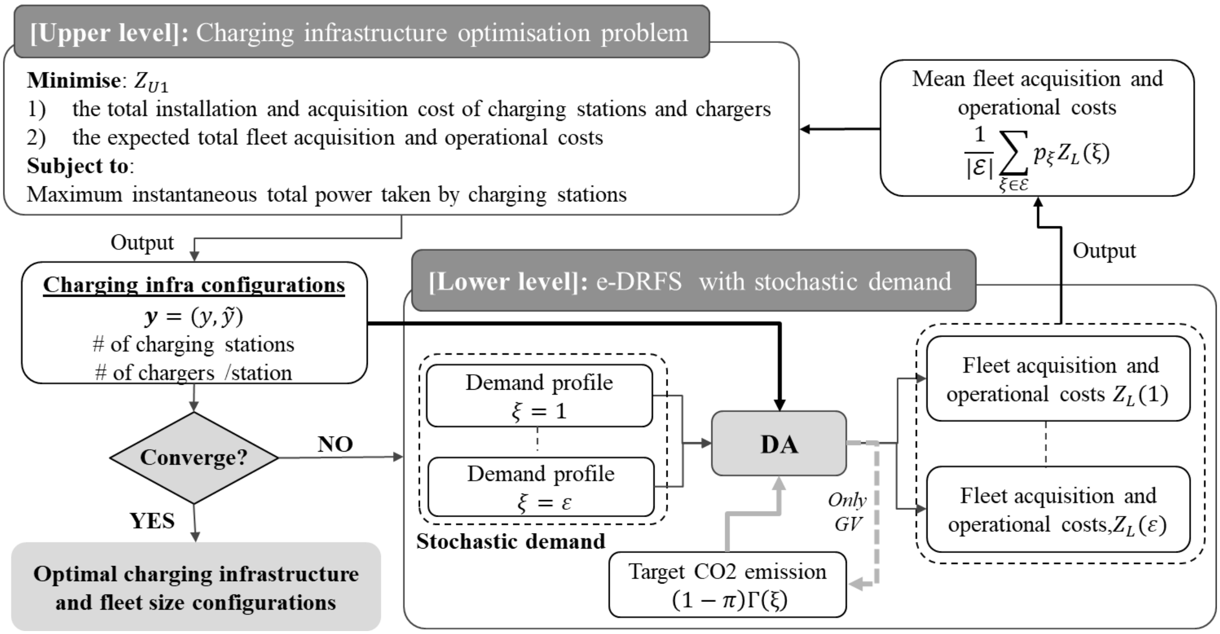

Figure 1 The bi-level problem framework

3. NUMERICAL EXPERIMENTS

Two numerical experiments are conducted to evaluate the performance of the DA-based metaheuristics and to demonstrate it can efficiently solve the proposed bi-level optimisation problem. The service network is assumed to be 16km^2 square with one train station and one depot equipped with overnight chargers. The train is assumed to be operated from 6 am to 11 pm with different intervals (i.e., 15, 30, 60min) reflecting the travel demand. DRFS provides first- and last-mile services to/from the train station where users can be picked-up/drop-off at the potential stops. The potential stops are uniformly distributed at a 1km distance apart. The maximum user waiting time at the station is set as 10 min. The detour factor to determine the maximum in-vehicle time is set as 1.5. Service time at the stop is assumed to be constant and 30 seconds.

Two potential charging stations are assumed where one station (CS1) has lower installation costs and can accommodate maximum 2 fast chargers with 50kWh power while another station (CS2) has higher installation costs but can accommodate up to 2 superfast chargers with 220kWh power. Fleet and charging infrastructure configurations are summarised in Table 1.

Table 1 The fleet and charging infrastructure configuration (based on Meishner and Sauer (2020))

Fleet types	**EV**	**GV**
Vehicle Capacity	24	24
Fuel Capacity (kWh) or (l)	117	-
Energy consumption rate (kWh/km) or (l/km)	0.938	0.002
Energy cost (€/kWh) or (€/l)	0.23	1.83
Daily equivalent of purchasing and maintenance cost (€/day)	23.78	16.17
Average speed (km/h)	50	50
CO2 emission (g/km)	0	0.176
Charging stations	**CS1**	**CS2**
Max number of chargers	2	2
Charging station opening cost (€/day)	4.11	68.08
Cost of rapid charger (€/day)	9.59	19.18
Charing power (kW/min)	0.83	3.67

Assuming that two chargers are installed at CS1, the LP is solved by a proposed DA-based metaheuristic and by a state-of-the-art MILP solver (Gurobi, version 10.0.0) with a 4h computational time limit. In total, 5 sets of instances are tested with 10 to 50 requests assuming 1 to 4 passengers per request. We run the experiments on a laptop with Intel(R) Core (TM) i7-11850H processor and 32 GB memory using up to 8 threads when solving the MILP in parallel. The results show that the DA-based metaheuristics provide the solution with a maximum of 1.05% gaps from best known objectives (BKO) with less than 2 second computational times on average. The large instances with 500 requests are solves with 82 seconds on average without CO2 constraints (GVs only). With the CO_2 constraint, the targeted CO_2 reduction level and the charging stations' configuration determine the computational time.

Using the DA algorithm tested above, the bi-level optimisation problem is solved with a 90% emission reduction target. Five demand scenarios with 100 requests are generated where the distribution of pickup and drop-off locations varies. Table 2 summarises the BKO for the LB, fleet size composition, and CO_2 emission for each demand scenario as well as the BKO for UP given each charging infrastructure configuration.

According to Table 2, the upper-level objective value is minimum when the number of chargers at CS1, CS2 is (CS1, CS2) = (1,0). Under this charging infrastructure configuration, the 90 percentile of CO_2 emission target is satisfied when the fleet composition is (GV, EV) = (0,6). It can be observed that less fleet is required if the greater number of chargers and/or the charger with the higher power are installed. In addition, more GVs tend to be used as the number of charger increases. It is because the greater number of chargers give EVs more freedom in their charging decisions which allows to utilise GVs as much as possible within the CO_2 emission threshold. As GVs are assumed to be cheaper to operate, this is consistent with our expectations.

Figure 2 shows that introducing one charger at CS1 does not reduce BKO for LP in scenario 2 as much as scenario 4. Besides, when chargers are installed as (CS1, CS2) = (1,1), BKO for LP have the lowest value for scenario 4 unlike scenario 2. These findings indicate that the proposed model effectively accounts for the influence of demand stochasticity on the effects that identical charging configurations can produce. Scenario 2 and 4 are selected in Figure 2 as they illustrate the impact of demand stochasticity more clearly than scenario 1 and 3.

Table 2 The results of bi-level optimization problem

Number of chargers			Demand scenario	Fleet size		Best obj for LP	Best obj for UP	CO2 emission
Total	CS1	CS2		GV	EV			
0	0	0	1	0	6	348.47	356.14	0.00
			2	1	6	365.13		17.87
			3	1	6	361.68		18.27
			4	0	6	348.73		0.00
			5	0	6	356.69		0.00
1	1	0	1	1	5	324.72	353.01	16.06
			2	1	6	365.67		16.69
			3	0	6	360.59		0.00
			4	1	5	325.99		16.99
			5	1	5	319.56		16.66
	0	1	1	0	4	294.76	394.63	0.00
			2	1	4	322.93		18.31
			3	1	4	312.36		17.57
			4	1	4	303.39		16.43
			5	1	4	303.41		16.25
2	2	0	1	1	5	326.46	359.25	16.69
			2	1	6	367.77		17.96
			3	1	5	327.54		18.15
			4	1	5	332.65		16.58
			5	1	5	325.40		17.07
	1	1	1	1	4	303.77	413.87	16.85
			2	1	4	326.98		17.74
			3	1	5	331.60		17.14
			4	1	4	297.24		16.66
			5	1	4	304.99		16.56
	0	2	1	0	4	312.40	416.68	0.00
			2	1	4	316.99		18.13
			3	1	4	310.39		18.15
			4	1	4	302.86		16.51
			5	1	4	308.58		16.86

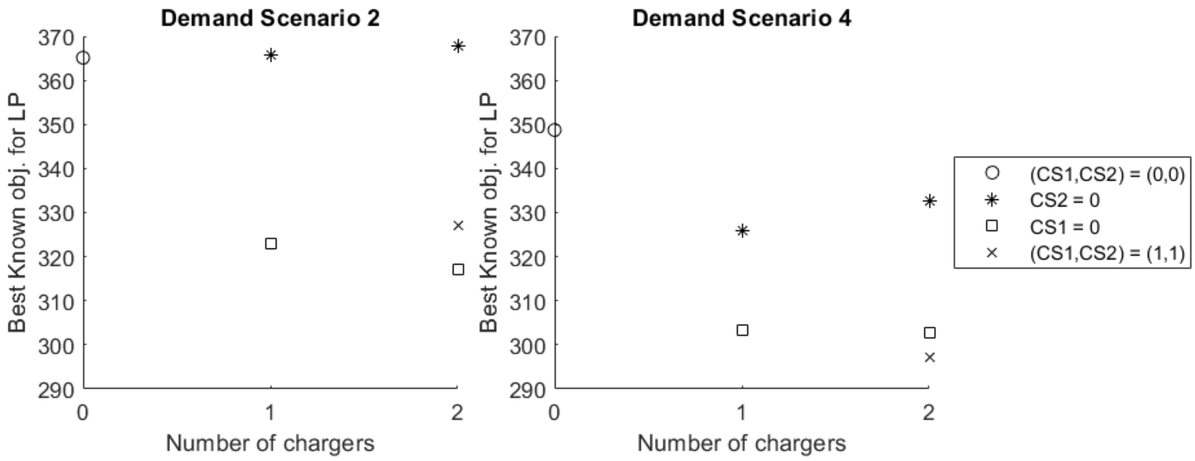

Figure 2 The BKO for LP with different charging configurations for scenario 2 (left) and 4 (right)

4. CONCLUSION

Joint considering the trade-off of CO_2 reduction target and the fleet electrification investment cost is an important decision issue for many mobility service operators. This study enables this configurable CO_2 reduction target as a lever for the joint fleet size and charging infrastructure planning of EV-based DRFS under stochastic demand. Future research directions include sensitivity analysis, increasing the problem size, and integrated DRFS with mass transit system optimization.

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