Coordinated vehicle dispatching and charging scheduling for electric ride-hailing fleet under charging congestion

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1 Introduction

Managing electric vehicle fleet dispatching and charging operations under uncertainty has been a challenging issue for ride-hailing service operators in recent years. As the number of fast charging infrastructure is limited due to its high investment costs, the operator needs to optimize their utilization to reduce vehicle queuing at charging stations. Uncoordinated vehicle dispatching and charging operations would result in significant revenue loss for the operator.

Methodologies developed in the past years are mainly based on a mixed integer programming optimization approach. The problem is decomposed into sequential sub-problems over different planning horizons for vehicle dispatching, relocation, and charging scheduling. For example, Jamshidi et al. (2021) proposed a three-stage sequential MILP model to address this problem. However, waiting time at the charging station is approximated without explicitly modeling charging queuing time on different chargers. Zalesak and Samaranayake (2021) developed a two-stage optimization approach to determine when to change over a longer planning horizon and where to charge over short planning horizons. They aim to maintain a sufficient fleet size to meet stochastic customers' demands and satisfy vehicles' charging needs. However, their study does not consider heterogeneous charging infrastructure and time-dependent energy prices.

2 METHODOLOGY

Consider a fleet of e-taxi in a service area operated by a transport company. Vehicle dispatching and charging operations (when, where, and how much energy to charge) are controlled by the operator's control center based on vehicle's real-time communication devices. The operator owns several fast/slow chargers at different locations. Vehicles are fully recharged during the night (e.g. 00:00 – 6:00 a.m.) on either public or operator-owned (private) chargers. During the service hours, vehicles can be recharged exclusively on private chargers. Time-of-use electricity prices are assumed, and no overlap is allowed on each charger for vehicle recharging. Similar to the current ride-hailing system, the operator matches unserved customers for each batch assignment epoch (e.g., 1 minute). Vehicles' state of charge (SoC) needs to be maintained above a minimum level (e.g. 10% of their battery capacities) all the time. The objective of the operator is to maximize the total profit of the e-taxi for the planning horizon (e.g., 6:00-24:00) under stochastic customer demand.

We propose a sequential optimization model (called **CongestionAware**) with three components. The first is a **vehicle dispatching** model to maximize the net profit of batch dispatch under the constraints of maximum waiting time of customers and energy feasibility of vehicles. The second is the **day-ahead charging planning** model, which determines when to charge and the targeted SoC of vehicles over the planning horizon based on time-of-use energy prices and expected waiting times on individual chargers. This plan is adapted based on a **reactive model** during the day according to actual vehicle charging needs and availability constraints of chargers based on the current system state. This reactive model maintains a pool of to-charge-vehicles based on the charging plan, which is adapted with additional vehicles to recharge (either with low SoC (i.e. less than 20% of their battery level) or previously delayed vehicles for charging when the number of to-charge-vehicles exceeds the number of chargers). An **online vehicle-to-charger assignment** model is applied to minimize total charging operation times. The planning horizon is discretized into a set of charging decision epochs H^{ℓ} with homogeneous intervals (e.g. 20 or 30 minutes). This plan guides vehicles' charging decisions over the planning horizon. We assume the system is cleaned after 00:00. To save charging time during the day, we avoid recharging vehicles to above 80% of their battery capacities as charging speed slows down above this level (Zalesak and Samaranayake, 2021). Each charging operation requires a minimum charging time (e.g. at least 10 minutes). Vehicles need to wait for available chargers if they are occupied. The day-ahead charging planning problem is formulated as a mixed integer programming problem as follows.

$$\min Z_2 = \sum_{v \in V} \sum_{h \in H^{\ell}} \sum_{s \in S} \left((p_h + \frac{\gamma}{\varphi_s}) y_{hs}^v + (C + \gamma \overline{W}_{hs}) x_{hs}^v \right) \tag{1}$$

s.t.

$$\textstyle\sum_{s \in S} x_{hs}^v \leq 1, \forall v \in V, h \in H^{\ell} \tag{2}$$

$$\sum_{v \in V} x_{hs}^v \leq 1, \forall s \in S, h \in H^{\ell} \tag{3}$$

$$e_{v,h+1} \leq e_{vh} - \delta_h \left(1 - \sum_{s \in S} x_{hs}^v \right) + \sum_{s \in S} y_{hs}^v, \forall v \in V, h \in H^{\ell} \tag{4}$$

$$e_{v,h+1} \geq e_{vh} - \delta_h \left(1 - \sum_{s \in S} x_{hs}^v \right) + \sum_{s \in S} y_{hs}^v, \forall v \in V, h \in H^{\ell} \tag{5}$$

$$\alpha_s \leq (\frac{y_{hs}^v}{\varphi_s}) + M_1(1 - x_{hs}^v), \forall v \in V, h \in H^{\ell}, s \in S \tag{6}$$

$$E_v^{min} \leq e_{vh} \leq E_v^{max}, \forall v \in V, h \in H^{\ell} \cup \{n_{H^{\ell}} + 1\} \tag{7}$$

$$e_{v1} = E_0, \forall v \in V \tag{8}$$

$$y_{hs}^v \leq M_1 x_{hs}^v, \forall v \in V, h \in H^{\ell}, s \in S \tag{9}$$

$$0 \leq y_{hs}^v \leq Y_s^{max}, \forall v \in V_h, h \in H^{\ell}, s \in S \tag{10}$$

$$x_{hs}^v \in \{0,1\}, \forall v \in V, h \in H^{\ell}, s \in S \tag{11}$$

The objective function (1) minimizes total charging costs of the fleet V on a set of chargers S (fast and slow chargers) over the planning horizon H^{ℓ}. Decision variables x_{hs}^v and y_{hs}^v denote whether vehicle v goes recharge at charger s at the beginning of charging decision epoch h and the amount of charged energy, respectively. h starts from 1, denoting the first charging decision epoch with SoC lower than E_v^{max} (80% of battery capacity) based on the average energy consumption δ_h of vehicles. The first term in Eq. (1) is related to charging costs for y_{hs}^v where p_h denotes the average energy price on h. φ_s is the charging power of charger s. γ is the average profit per vehicle-minute traveled. The second term is related to charging access distance costs C and expected waiting times $\overline{W}_{hs}$ when arriving at the charger s at the beginning of epoch h. Eqs. (2) and (3) state that each vehicle can be assigned to at most one charger, and each charger can be assigned to at most one vehicle for each h, respectively. Eqs. (4) and (5) state vehicles' SoC changes from h to $h+1$ with the charged amount of energy when recharging and with average energy consumption δ_h of vehicles for serving customers. Eq. (6) states that a minimum charging time α_s is implied for each charging operation. Eq. (7) and (8) set the range of e_{vh} and the initial battery level E_0 at $h = 1$, respectively. Eq. (9) binds x_{hs}^v and y_{hs}^v with a big positive number M_1. Eq. (10) ensures the maximum amount of energy can be recharged from charger s during one charging decision epoch. The model parameters δ_h, $\overline{W}_{hs}$, γ, and C can be estimated based on historical vehicle driving and charging data.

3 COMPUTATIONAL RESULTS AND DISCUSSION

To validate the proposed approach, NYC yellow taxi data on a typical weekday in July 2019 is used. Customers' arrival times are sampled from the data. As the dataset does not contain their pickup and drop-off locations, we randomly generated a Manhattan-like rectangle area of 4X20 km2 with a minimum trip length of 5 km where the trips' origin or destination could be outside this area. The fleet size is assumed 100 Nissan Leaf e+ electric vehicles with 62kWh battery capacity. The energy consumption rate is 0.25 kWh/kilometer traveled. We assume that there are six (operator-owned) DC fast chargers (50 kW) and six slow chargers (11 kW) on four different charging stations. Electricity prices are based on day-ahead electricity prices and vary every 15 minutes. We consider different demand scenarios ranging from 3000 to 4000 requests/day. For each scenario, we generate 15 independent datasets where 10 datasets (corresponding to 10 past days' demand) are used for estimating the model parameters, and the rest 5 data sets are used for validating the performance of our approach. A more detailed description of the test instances can be found in Ma et al. (2024).

Four benchmark charging policies are compared, including the Nearest charging policy (Nearest), the Fastest charging policy (Fastest), the Charging operation time minimization approach (MinChgOpT) (Ma and Xie, 2021), and the Dynamic charging threshold policy (DynaThreshold) (Ahadi et al., 2022). All the benchmark policies apply an 80%-full charging policy for vehicle recharging during the day. The nearest policy assumes vehicles go to the nearest charging station. The fastest policy assigns vehicles randomly to the fastest chargers to avoid over-congested utilization of certain fast chargers. MinChgOpT policy assigns vehicles to the charger with minimum charging operation time, considering vehicle access time to chargers, waiting time at chargers when arriving there, and charging time. The above three policies assign vehicles to charge when vehicles' SoC is below 20%. DynaThreshold anticipates higher charging waiting time in the afternoon (more vehicles need to recharge and flash to the limited number of fast chargers) and applies pre-defined dynamic thresholds on an hourly basis to reduce charging congestion of the fleet. For the benchmark policies, a maximum charging waiting time (e.g., 15 minutes) is applied when vehicles wait to charge in a queue. When the queuing length is too long, vehicles go to another charger with the least waiting time. However, when vehicles' SoC is too low to move to another charger (vehicles need to keep a minimum SoC of 10%), vehicles remain waiting in the queue for charging. The day-ahead charging planning model is solved by Gurobi with 1 or 2 hours of computational time to obtain approximate solutions (~10% optimality gaps), and the computational studies are implemented in Julia.

Two demand scenarios with 3000 and 4000 requests are tested. The results are shown in Table 1. We observe that the CongestionAware outperforms the benchmark approaches with higher profit with +5.75% and +5.53% for c3000 and c4000, respectively, compared to the second-best DynaThreshold policy). For the c3000 scenario, the charging waiting time of the CongestionAware policy is much smaller (-50% or more) compared with the benchmark. For the c4000 scenario, the charging waiting times become much higher due to more additional low-SoC vehicles for recharging, given a very high demand (customer service rate drops from 95.8% to 74.9% for c4000). For the c3000 scenario, Figure 1 (on the left) reports the average experienced charging time on each fast charger using the 10 test instances based on the Fastest charging policy. It increases drastically during 16:00 -20:00 with different profiles due to their different geographical locations and customer demand distributions. From the number of vehicles charging (on the right of Figure 1) and number of vehicles waiting (for charging) (on the left of Figure 2), we can observe that the CongestionAware shifts vehicles charging operations earlier (with shorter charging times), resulting in lower waiting times compared to the benchmark. Figure 2 (on the right) compares the SoC of vehicles over time for the CongestionAware and DynaThreshold policies. It shows vehicles' SoC distribution is maintained at lower levels for the CongestionAware policy near the end of the day.

Table 1 – *Comparison of key performance indicators for different charging policies.*

Scenario	Charging policy	PF	TR	SR	TTC	CC	ENG	KMT	TW	TC
c3000	Nearest	73.95	90.14	87.0%	14.95	0.93	2961	28.21	106	98
(3000	Fastest	73.73	89.90	86.8%	14.90	0.94	3005	28.12	98	96
requests)	MinChgOpT	74.91	91.32	88.5%	15.13	0.97	3133	28.55	99	97
	DynaThreshold	75.81	92.97	90.3%	15.45	1.08	3499	29.15	112	112

	CongestionAware	**80.16**	**97.49**	**95.8%**	**16.03**	**0.82**	**2589**	**30.24**	**46**	**57**
c4000 (4000 requests)	Nearest	76.72	93.25	65.5%	15.51	0.82	2652	29.27	138	94
	Fastest	77.63	94.44	67.0%	15.71	0.87	2979	29.64	139	99
	MinChgOpT	77.52	94.22	66.7%	15.67	0.83	2869	29.56	99	91
	DynaThreshold	81.78	100.23	70.0%	16.72	1.12	3754	31.54	128	122
	CongestionAware	**86.30**	**106.13**	**74.9%**	**17.78**	**1.30**	**4205**	**33.55**	**233**	**123**

Remark: PF: profit; TR: revenue; SR: service rate; TTC: travel costs; CC: charging costs; ENG: total charged energy (kWh); KMT: total vehicle-kilometer traveled; TW: Total charging waiting time; TC: total charging time. Profit, revenue, costs, and KMT are dollars or kilometers in thousands. Charging time and charging waiting time are in hours.

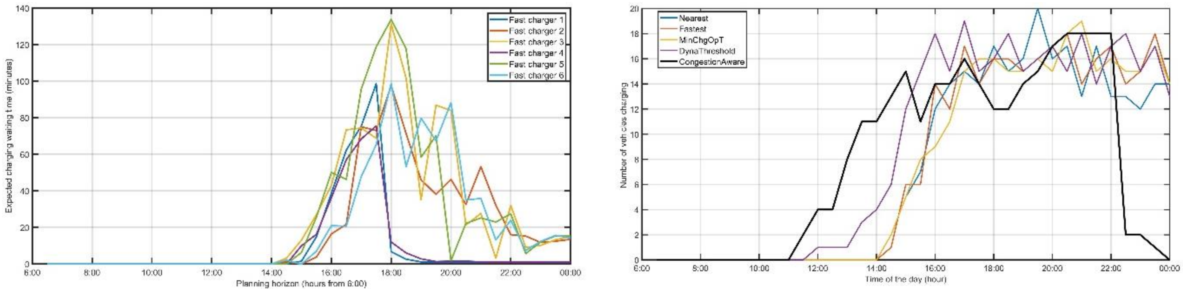

Figure 1 – *Expected charging waiting time on chargers (Left) and the number of vehicles charging during the day for different charging policies (Right)(# of customers=3000).*

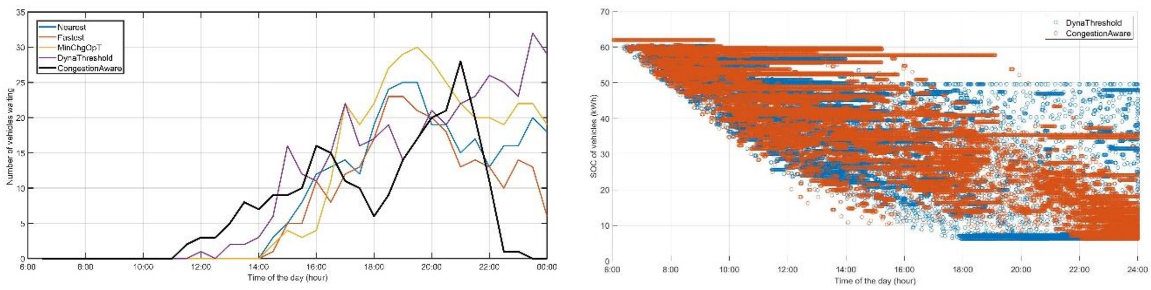

Figure 2 –*Number of vehicles waiting during the day for different charging policies (Left), and SoC of the fleet over time (# of customers=3000).*

4 CONCLUSIONS

This study develops a sequential optimization approach to coordinate vehicle dispatching and charging operations for e-taxi fleet management under stochastic demand, variable energy prices, and congested charging facilities. We conduct a simulation case study using NYC taxi data. The computational results show the developed methodology outperforms several benchmark approaches with higher profit and customer service rates under different scenarios (demand intensities, battery capacity, fleet size/charging facilities). This methodology can be applied to support transport network companies for more efficient management of customer services and charging operations.

References

Ahadi, R., Ketter, W., Collins, J. & Daina, N., 2023. Cooperative learning for smart charging of shared autonomous vehicle fleets. *Transportation Science*, *57*(3), pp.613-630.

Jamshidi, H., Correia, G.H., van Essen, J.T. & Nökel, K., 2021. Dynamic planning for simultaneous recharging and relocation of shared electric taxies: A sequential MILP approach. *Transportation Research Part C*, *125*, p.102933.

Ma, T. Y. & Xie, S., 2021. Optimal fast charging station locations for electric ridesharing with vehicle-charging station assignment. *Transportation Research Part D*, *90*, 102682.

Ma, T.Y., Connors, R.D. & Viti, F., 2024. Congestion-Aware Charging Management for Ride-Hailing Systems with Time-Varying Energy Prices. In: ICSSE2024, IEEE, pp. 1-6 .

Zalesak, M. & Samaranayake, S., 2021. Real-time operation of high-capacity electric vehicle ridesharing fleets. *Transportation Research Part C*, 133, pp.103413.