Congestion-aware charging management for electric ride-hailing systems with time-dependent energy prices

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SHORT SUMMARY

Dynamic charging management of electrified ride-hailing services under a stochastic environment is a challenging research issue due to the interplay between vehicles' decisions for serving customers versus charging operations. Existing studies assume constant energy prices and uncapacitated charging stations or do not explicitly consider vehicle queueing at charging stations, resulting in over-optimistic charging infrastructure utilization. This work develops a mixed integer linear program to optimize the sequential decision problems of dynamic ride-hailing systems to maximize the operator's profit under time-varying energy prices. We tested the proposed method on different scenarios using 2019 NYC yellow taxi data. The results show that the proposed methodology can (i) increase the profit and service rate (+5.72% to +21.6% and +5% to +17.9%, respectively), (ii) reduce total electricity cost for charging by at least 52.6% compared with the four benchmark approaches (100 EVs and 3500 customers/day), (iii) significantly reduce vehicle waiting time at charging stations under a heterogeneous charging station environment.

Keywords: ride-hailing, electric vehicle, charging management, time-of-use energy prices, optimization

1. INTRODUCTION

The climate change crisis has motivated governments and Transport Network Companies to accelerate the fleet electrification to reduce CO2 emissions. Charging management is becoming a significant issue for this clean air transition due to the long charging times of electric vehicles (EVs), compared to refuelling an internal combustion engine vehicle, in addition to limited availability of public charging stations. However, the high daily mileage of TLC's vehicles necessitates drivers charging their vehicles several times a day, relying mainly on rapid chargers to save charging time (jenn, 2019). Optimizing the utilization of limited fast-charging resources in a stochastic environment has become a major challenge for this EV transition.

Several factors make dynamic charging management of electric ride-hailing systems challenging. First, customer demand is volatile, affecting vehicles' charging needs over time. Second, rapid chargers (charging power >=50kWh) are limited due to their high investment costs. This might result in EVs queuing at charging stations, thereby increasing charging station search costs for the drivers. Furthermore, charging costs might vary according to the time of day due to variations in electricity prices. The decision on when and how much energy to recharge becomes an important online decision problem for drivers/fleet operators to maximize their profit. However, most studies assume constant energy prices and neglect congestion issues at charging stations (Iacobucci et al., 2019; Zalesak and Samaranayake, 2021, Ma 2021; Jamshidi et al., 2021).

This work presents a novel dynamic charging schedule optimization for electric ride-hailing systems as a sequential decision problem under uncertainty. A two-stage planning approach is developed by optimizing the day-ahead vehicle charging schedules based on the expected energy consumption and waiting time at charging stations in the first stage. The plan is re-optimized online by considering the interactions of customer arrivals, vehicle energy consumption, and charging operation time.

2. METHODOLOGY

Consider a ride-hailing system providing a taxi-like service with a fleet of EVs in a service area. A centralized controller (operator) controls vehicle dispatching and charging decisions. Customers arrive stochastically following some unknown probability distribution. Vehicles' charging operations can only occur at the operator-owned charging stations, and the charging facilities are heterogeneous. We explicitly model the queueing of vehicles at each charger level, where the occupancy of each charger is monitored in real time. Regarding energy costs, we consider that electricity prices vary with the time of the day. The operator aims to maximize the fleet's profit from serving customers over a planning horizon.

2.1. Vehicle dispatching

We propose a batch dispatch optimization approach to match unserved requests and idling vehicles every batch decision epoch. The objective of the proposed dynamic charging methodology aims to address this issue to enhance the charging operation efficiency, reduce charging costs and maximize the profit of the system. We call the proposed method the **congestion-aware charging policy**. The dynamic charging management problem is decomposed into two levels: day-ahead charge schedule planning and sequential short-term vehicles' charging decisions based on the current system state. We assume that vehicles comply entirely with the planned charging schedule. Algorithm 1 depicts the overall charging planning, vehicle-charger assignment, and batch dispatch to maximize the system's profits.

Algorithm 1. Dynamic charging planning, vehicle-charger assignment, and batch dispatch.

Compute the historical energy consumption and experienced charging waiting times of vehicles

Solve day-ahead charge planning problem (M2) to get initial charge plans of vehicles

Initialization

For $t = t_0 : T$

    Update the list of unserved customers

    For each vehicle-charger assignment decision epoch h (i.e., $t\%\Delta_l = 0$)

        Collect vehicles planned to be recharged on h and add them in the pool of uncharged vehicles

    End

    Get the subset of uncharged vehicles that are idled currently and run the vehicle-charger assignment algorithm (M3)

    Run the batch dispatch algorithm (M1)

    Update the system state

End

2.2. Charge schedule planning and online vehicle charging decision management

The day-ahead charge schedule planning aims to decide when and how much energy to recharge for each vehicle by taking into account time-varying energy prices, historical vehicle energy consumptions, and charging station capacity constraints. The entire planning horizon is divided into a set of charging decision epochs with uniform time interval Δ_ℓ. Charging speed, charging station capacity and experienced waiting time at charging stations at previous days are considered explicitly to devise an initial charging plan.

(M2): Day-ahead charge schedule planning

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

Subject to

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

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

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

$$\alpha B_v \leq y_{hs}^v + M_1 (1 - x_{hs}^v), \forall v \in V, h \in H^\ell, s \in S^{\text{fast}} \tag{5}$$

$$E_v^{min} \leq e_{vh} \leq E_h^{max}, \forall v \in V, h \in H^\ell \tag{6}$$

$$e_{v0} = E_{v0}, \forall v \in V \tag{7}$$

$$y_{hs}^v \leq M_1 x_{hs}^v, \forall v \in V, h \in H^\ell, s \in S \tag{8}$$

$$0 \leq y_{hs}^v \leq Y_s^{max}, \forall v \in V_h, h \in H^\ell, s \in S \tag{9}$$

$$x_{hs}^v \in \{0,1\}, \forall v \in V, h \in H^\ell, s \in S \tag{10}$$

The objective function (1) minimizes total system costs related to charging operations. The first term is the total electricity cost and net profit loss of vehicles' charging operations. The second term is the summation of vehicles' travel costs to reach charging stations and waiting time costs for recharging. Eqs. (2) and (3) ensure that each vehicle (charger) can be assigned to at most one charger (vehicle) for each decision epoch. Eq. (4) states vehicles' SOC evolution from one decision epoch to another. For each decision epoch, a vehicle's SOC is updated if it gets recharged at a charger s by y_{hs}^v. Otherwise, its SOC is reduced by the average energy consumption when serving customers δ_h. Eq. (5) states that a minimum charging amount is required to use a fast charger. Eqs. (6) and (7) set up vehicles' initial SOC and value range. Eq. (8) binds the decision variables x and y. Eq. (9) ensures that the maximum amount of energy that can be charged during one epoch. Note that two parameters are used for day-ahead charge planning, i.e., the average profit per vehicle per minute traveled γ and the average energy consumption per vehicle for each epoch h. This information can be easily obtained based on historical driving patterns of vehicles and the time series modeling approach.

The **online vehicle charging decision** problem aims to execute the day-ahead charging plans for each charging decision epoch $h \in H^\ell$. An MILP model is proposed to optimize effectively vehicle-to-charger assignment to minimize the total charging operation times under congested charging network.

3. RESULTS AND DISCUSSION

3.1. Test instance

We test the proposed dynamic charging planning approach on a 4X20 km^2 area, which is similar to the shape and size of Manhattan. We assume that the electric ride-hailing services operate from 6:00-24:00 a day. Vehicles are initially located randomly in the study area (see Figure 1). Customer arrivals are randomly drawn from the trips of New York yellow taxi data on a typical weekday. We consider a fleet size of 100 homogeneous EVs. Three demand intensity scenarios are considered, i.e., 3000, 3500, and 4000 requests. Battery capacity and energy consumption are based on characteristics of the Nissan Leaf e+. The charging cost for the operator is based on the time-varying day-ahead electricity prices, adapted to the real charging fee of NYC public charging stations. The numbers of chargers and charging stations are shown in Figure 1.

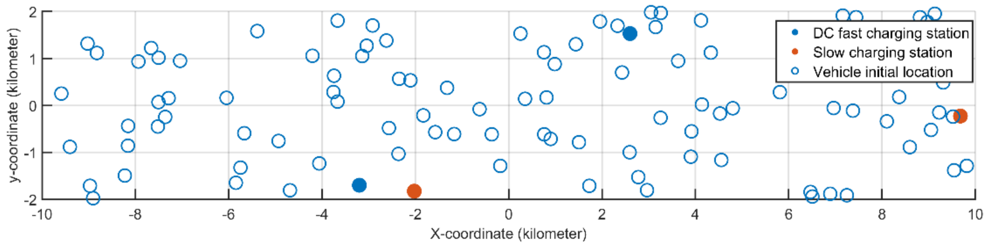

Figure 1. Charging station distribution in the study area. There are 4 charging stations, each with three chargers of the same type. A total of 6 DC fast chargers (50kW) and 6 slow chargers (11kW).

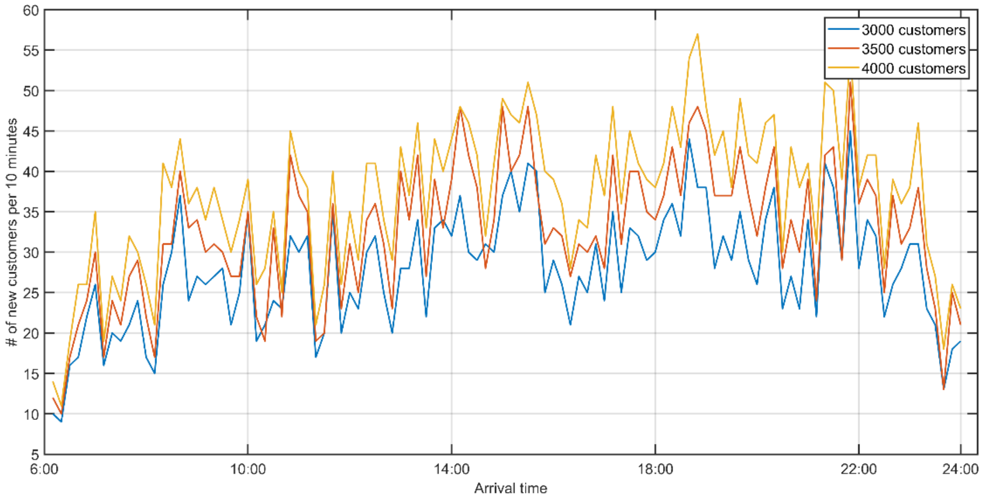

Figure 2. Customer arrival intensity per 10 minutes for three different demand scenarios.

3.2. Results

To validate the proposed methodology (named **CongestionAware**), four benchmark approaches are compared.

a. Nearest charging policy (**Nearest**): Vehicles go to the nearest charging station to recharge to 80% when their SOC is less than 20% of their battery capacity (Bischoff and Maciejewski, 2014).
b. Fastest charging policy (**Fastest**): Vehicles use the fastest charger to recharge to 80% to save their charging time. This policy applies when the vehicles' SOC is below 20%.
c. Charging operation time minimization approach (**MinChgOpT**) (Ma and Xie, 2021): When a vehicle's SOC is below 20%, assign the vehicle to the charger with mínimum charging operation time.
d. Dynamic charging threshold policy (**DynaThreshold**): This policy utilizes time-dependent thresholds (change per hour) by considering customers' arrival rate to give priority to serving customers (Ahadi et al., 2022).
e. ICE (Upper bound): The internal combustion engine (**ICE**) fleet is used instead of EVs.

The results are shown in Table 1. We can observe that the proposed method outperforms the four benchmark charging policies. The profit is $86.2K, which is 5.72% to 21.6% higher than the benchmarks. The service rate is 98.2%, which is around 5% to 17.9% higher compared to the bencharks. The nearest charging policy performs worst as it does not take into account chargers' speed when going to charge. In terms of waiting time and charging cost, we can find that the proposed charging policy significantly reduces charging congestion and saves charging costs. The total charging cost is $0.51K, while the other policies are almost three times more costly, or worse. Total waiting time is only 2.4 hours, while other policies have large waiting times due to many unplanned charging operations. Figure 4 compares the numbers of vehicles charging per hour for different charging policies. We can find that the Nearest, Fastest, and MinChgOpT policies start charging vehicles near 18:00, resulting in a significant increase of vehicle queueing at the DC fast charging stations (Figure 4). The DynaThreshold has a less peaked but wider profile for vehicles charging from 14:00 until the next day (Figure 3). The number of vehicles waiting (queuing) increases significantly after 18:00 due to a limited number of DC fast chargers. On the contrary, we can find that vehicles go charging mainly between 13:30 and 19:30 for CongestionAware policy. It allows us to avoid charging congestion at the end of the day. Furthermore, electricity prices are lower during this period. No overnight charging is observed compared to the other policies. The results show that the benefits of the proposed charging congestion management method increases the operator's profit and vehicle availability with better utilization of charging facility and reduced charging costs.

Table 1. Comparison of KPIs for different charging policies.

Charging policy	Profit	SR	TR	TTC	CC	KMT	TC	TW
Nearest	70.9	80.3%	85.2	12.9	1.30	24.3	178.8	1634.6
Fastest	78.9	89.6%	94.9	14.4	1.30	27.2	85.1	380.7
MinChgOpT	80.0	91.1%	96.1	14.6	1.24	27.5	119.1	226.3
DynaThreshold	81.5	93.5%	98.3	14.9	1.47	28.1	97.0	385.2
CongestionAware	**86.2**	**98.2%**	**102.1**	**15.1**	**0.51**	**28.5**	**33.6**	**2.4**
ICE (upper bound)	87.5	98.5%	102.4	14.9	0.00	28.0	0.0	0.0

Remark: SR: service rate; TR: Revenue; TTC: travel costs; CC: charging costs; KMT: total kilometer traveled; TC: total charging time (hours). TW: Total charging waiting time. Profit, revenue, costs, and KMT are dollars/kilometers in thousands. Charging time and charging waiting time are in hours.

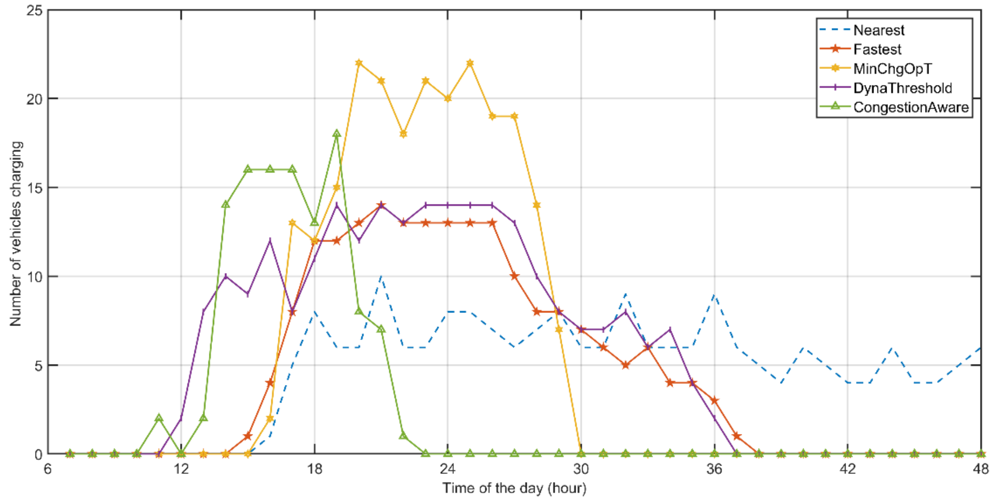

Figure 3. Comparison of number of vehicles charging per hour for different charging policies.

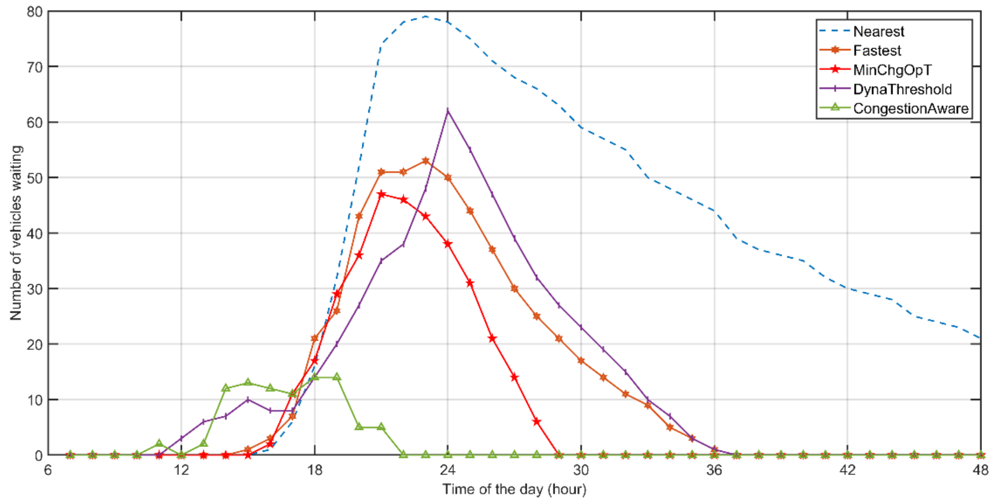

Figure 4. Comparison of number of vehicles waiting per hour for different charging policies.

4. CONCLUSIONS

This study proposed a novel two-stage MILP-based dynamic charging management approach to increase the efficiency of vehicle charging operations in ride-hailing systems with time-varying electricity prices and capacitated charging stations. The results show that the proposed methodology can increase significantly the profit and service rate and reduce total electricity cost for charging compared to the best of four benchmark approaches with a fleet of 100 EVs and 3500-4500 customers a day.

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