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Coordinated Scheduling of EV Charging Service and Energy Arbitrage for Truck Mobile Charging Stations

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Abstract—Truck mobile charging stations (TMCS) have emerged as a promising complement to fixed charging stations (FCS), sparking increased interest in recent years. However, the potential applications of TMCS have yet to be fully explored, which impedes its economic feasibility and widespread adoption. Therefore, this paper aims to address this gap by proposing a two-stage scheduling model for TMCS, focusing on coordinating its operation between electric vehicle (EV) charging services and energy arbitrage. In this model, an EV charging demand generation model is formulated to capture the charging behavior of EV users between FCS and TMCS. Additionally, an extended graph model is developed to depict the dynamic characteristics between different service provisions of TMCS. To account for the impact of EV charging demand uncertainty on operator profit, a two-stage optimal scheduling model based on lookahead rolling horizon-value function approximation (LRH-VFA) is established. By offline learning from historical data, the impact of current decisions on future periods is considered. Subsequently, using short-term forecast data and real-time information, the online optimization results are rolling updated and outputted. Numerical studies demonstrate that the proposed method can effectively enhance the utilization and economy of TMCS.

Index Terms—Truck mobile charging station, energy arbitrage, coordinated scheduling, value function approximation, profitability

NOMENCLATURE

Sets and indexes

$\mathcal{N}$	Set of traffic network nodes
$\mathcal{A}$	Set of traffic network links, i.e., $\mathcal{A} \subseteq \mathcal{N} \times \mathcal{N}$
$\mathcal{E}$	Set of distribution network nodes
Ω	Set of TMCS, indexed by ω
$\Omega_m^{c,t}$	Set of TMCSs that are involved in charging service provision at node m
M	Set of TMCS operating locations
M_c	Set of charging service nodes, i.e., $M_c \subseteq \mathcal{N}$
M_a	Set of energy arbitrage nodes, i.e., $M_a \subseteq \mathcal{E}$
X^t	Feasible set of decisions
$\chi_{t,m}^{\text{tmc}}$	Set of EVs choose TMCS for charging
Z_c^+	Charging arc that starts from a specific node

Z_a^-	Arbitrage arc reaches a specific end node
m, u	Candidate locations for charging service nodes
n, v	Candidate locations for energy arbitrage nodes
i	EV index
j	Charging scheme index
a	Segment index
k	Iteration index
t	Time index
Δt	Time interval

Parameters

$v_A^{\max}$	The zero flow speed of section $\mathcal{A}$
$\mathcal{R}_A$	The traffic capacity of section $\mathcal{A}$
a_v, b_v, w	Road adaptability coefficients
$\mathcal{K}_{\text{pect}}$	Air conditioner opening rate
$\mathcal{K}_{\text{temp}}$	Temperature-energy consumption proportionality coefficient
$\mathbb{K}_1 \sim \mathbb{K}_4$	Fitting parameters
$\mathbb{C}_1 \sim \mathbb{C}_3$	Battery capacity
$\mathcal{M}_i$	Battery efficiency
η_t	Nominal energy consumption per kilometer
$\mathcal{C}_{ei}^{\text{N}}$	Energy consumption per kilometer considering air conditioning energy consumption
$\mathcal{C}_{ei}$	Remaining distance after charging of EV i
d_i	The mileage that EV i traveled when reaches node m
d_i^m	Redundant capacity conversion value of EV i considering user psychology
d_i^{rc}	Charging capacity obtained by MCS
$\mathbb{M}_i^{m,j}$	EV charging fee per kWh for charging scheme j at node m
σ_m^j	Rated power of the charger
P_r^j	Charging efficiency
η_{dch}	Operation time
s_c	Queuing time
$\mathbb{W}_q^{j,t}$	Monthly income of users
INC_i	Monthly average working hours of users
T_m	Time for TMCS to end operation
t_e	

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$P_{ch,\omega}^{\max}$	Maximum charging and discharging power of TMCS ω
$P_{dch,\omega}^{\max}$	Maximum power of TMCS ω in charging service
$P_{cs,\omega}^{\max}$	Hourly EV charging demand of TMCS and its prediction error
$P_m^t, \hat{P}_m^t$	EV charging demand satisfied ratio
ρ	Maximum and minimum SOC levels of TMCS
$SOC_{\max}, SOC_{\min}$	Charging and discharging efficiency of TMCS
$\eta_{ch,\omega}, \eta_{dch,\omega}$	Charging service fee and its prediction error
$\alpha_m^{tmc}, \hat{\alpha}_m^{tmc}$	Energy arbitrage charging price, discharging price and their prediction error
$\lambda_n^{t,c}, \lambda_n^{t,d}, \hat{\lambda}_n^{t,d}, \hat{\lambda}_n^{t,c}$	Charging price when TMCS ends operation and get charged
$\lambda_n^{t,c}$	Energy consumption per kilometer of TMCS
C_{tmc}	Labor and maintenance cost converted to time t
c^{la}, c^{mt}	Life-cycle marginal degradation cost to achieve the maximum life-cycle revenue of TMCS
c^{mdc}	Calendar degradation parameter of TMCS battery packs
q^t	Year order of time t since TMCS was put into service
$\kappa(t)$	Discount rate
r_0	Discount factor
γ	Rolling horizon
H	Total number of time slots within the scheduling horizon
T	Battery capacity
E_ω	Maximum and minimum energy storage capacity of TMCS
$E_\omega^{\max}, E_\omega^{\min}$	Total number of segments in PLF $\vec{V}_x(\cdot)$
N^a	Slope update step
θ_{k-1}	

Variables

v_A^t	The average speed of section A at time t
$\mathcal{Q}_A^t$	The actual flow of section A at time t
$\mathcal{U}$	Air temperature (Celsius)
$\mathcal{M}_i^{m,j}$	Charging capacity when EV i at node m chooses charging scheme j
$\zeta_{\omega,mu}^t$	Binary variable, 1 if TMCS ω lies on arc (m,u) at time t , and 0 otherwise
$I_{ch,\omega}^t, I_{dch,\omega}^t$	Binary variables, 1 if TMCS ω is charging or discharging in time t , and 0 otherwise
$D_{mn,\omega}^t$	Distance traveled by TMCS at time t
$P_{ch,\omega n}^t, P_{dch,\omega n}^t$	Charging and discharging power of TMCS ω at node n
x^t	Decision variables
$R, C_{\text{DEG}}^{\text{OM}}$	Revenue, O&M cost and the degradation cost
S_x^t	State variable after the decision
$V_x^t(\cdot)$	State of the system after a decision is executed but before any random information is received
SOC_x^t	SOC value of TMCS after the decision

$d_{a,\omega}^t$	Slope for segment a of PLF
$r_{a,\omega}^t$	Projection length of $SOC_x^{t+\Delta t}$ onto the horizontal coordinate in segment a
SOC_ω^t	SOC of TMCS ω before decision x^t is executed

I. INTRODUCTION

DRIVEN by the increasing number of electric vehicles (EVs), massive EV charging facilities need to be built to meet the growing charging demand. The latest *Global EV Outlook 2024* report from the International Energy Agency (IEA) shows that EV sales continue to rise. They will reach about 17 million by 2024, accounting for more than one-fifth of global vehicle sales. Meanwhile, the number of public charging facilities remains insufficient, necessitating a sixfold increase by 2035 [1]. In fact, some limitations remain challenging for conventional public fixed charging stations (FCS). Firstly, the peak of the EV charging load may overlap with the peak demand from decarbonizing heating using heat pumps, as well as residential loads. This can result in a further larger peak and call for system augmentation [2]. In addition, uncertainties in EV charging demand may lead to polarized utilization of FCS in practice. For example, some FCSs on highways may be crowded during holidays but quiet on weekdays [3]. Consequently, FCSs tend to be installed more in urban areas rather than rural or suburban areas. Moreover, the return on FCS investment is often inadequate due to high upfront costs, challenges in expansion or relocation, and a lack of flexible and efficient utilization schemes [4]. These barriers hinder the further expansion of FCS.

Emerging truck mobile charging stations (TMCS) are expected to offer novel solutions to address the above challenges. TMCS operates similarly to the power banks but for EVs instead of smartphones. It consists of a certain number of chargers and a utility-scale battery storage bank carried by truck [4]. TMCS are more flexible and scalable than FCS, reducing EV drivers' reliance on FCS by providing flexible charging services [2][4]. Tesla has launched TMCS with capacities up to 3MWh [5]. Volkswagen has delivered a dozen TMCS in Germany to offer DC fast charging and grid ancillary services like peak shaving and renewable energy storage [6]. Chinese automaker NIO recently announced plans to deploy 120 high-capacity TMCSs along highways in northwest and northeast China by 2024 [7].

At present, research on mobile charging stations is primarily divided into two categories. 1) A large part of this focused on the application of portable charging stations (PCS) in urban traffic scenarios. These studies addressed the PCS scheduling and routing problem by organizing routes and charging locations based on EV charging requests [2][8][9]. Additionally, PCS were applied to charge shared EVs [10], provide on-the-move charging service [11], and maximize the number of served EVs [12]. The PCS routing problem, fleet sizing and depot siting were studied [13]. By introducing different types of FCS and PCS, the overall charging costs and time spent of EV users were reduced [14]. A federated learning approach was adopted in [15] to predict potential charging loca-

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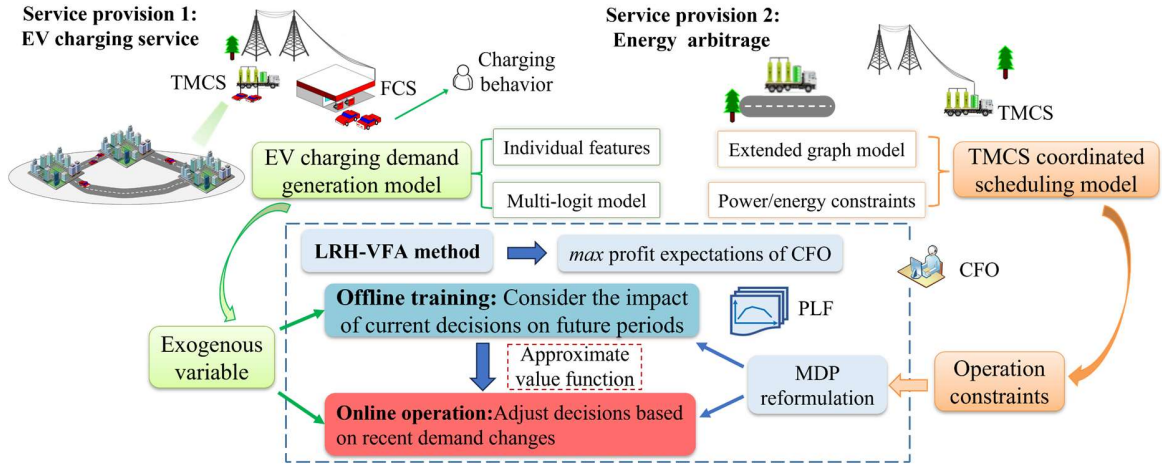


Fig. 1 The framework of two-stage scheduling model for TMCS.

tions and help idle PCSs move towards them earlier. These studies provide valuable insights into TMCS scheduling issues. However, there are gaps between PCS and TMCS in several performance aspects. The former primarily focuses on providing charging services based on individual charging requests, while TMCS can handle overloaded FCSs due to its more chargers and higher capacity.

2) Several studies explored the operation of TMCS. The flow-refuelling location model was adopted to optimize the service location of TMCS [16]. The peak load of FCS was significantly reduced by scheduling TMCS to move to specific areas [17]. TMCS was scheduled to charge during low electricity price periods and deployed to FCS during peak hours to provide EV charging services [18]. A greedy algorithm for assigning TMCSs to hotspot areas was proposed to support FCS [19]. The operation mode and service location of TMCS was determined based on queuing constraints [20]. However, none of these studies [16]–[20] considered the decision-making process of EV users between FCS and TMCS, nor did they analyze the impact of charging demand uncertainty on operator revenues. A mixed-integer linear programming (MILP) model was developed for TMCS scheduling and operator profit optimization and solved using an improved genetic algorithm [21]. The authors plan to conduct a follow-up study on charging demand uncertainty. The MILP approach was utilized to combine TMCS with integrated energy systems, where TMCS were charged at photovoltaic power plants [22]. Based on FCS and TMCS, a hybrid charging mode business model for EV charging stations was proposed, along with a corresponding pricing mechanism [23]. A deep reinforcement learning approach was employed to predict EV charging demand in a stochastic TMCS-based environment [24]. A cloud-based control framework and decision process were proposed to reduce the charging time of EVs by launching TMCS and peer-to-peer charging [25]. Additionally, some studies investigated the application of TMCS in EV parking lots and its social equity access [26], and auction-based energy trading strategies between EVs and TMCS [27]. Nevertheless, the focus of these works was primarily on EV charging services, without considering that TMCS may be underutilized, which may lead

to poor economics. This is also one of the main gaps between current academic research and practical applications [28]. To the best of our knowledge, there is no existing literature that focusing on the coordinated scheduling of TMCS under multiple service provisions. In particular, the flexibility of TMCS could be further explored to increase revenues during low utilization periods, e.g. by participating in grid ancillary services. In this area, there were studies on the application of mobile energy storage in energy arbitrage [29], renewable energy integration [30], and reactive power support [31], which provide valuable references. However, with the uncertainty of EV charging demand, it is critical to ensure the charging service quality. Consequently, scheduling TMCS efficiently in real-time to coordinate multiple service provisions and improve profitability remains a challenge.

In our previous study, we developed a bilevel planning framework to coordinate TMCS and FCS on highways, aiming to enhance charging flexibility [32][33]. As a follow-up work, this paper introduces a coordinated scheduling model for TMCS to integrate EV charging services with energy arbitrage. The contributions of this study are threefold:

- 1) Based on the EV charging demand generation model, the choice and charging behavior of EV users between FCS and TMCS are simulated. The dynamic transfer between different service provisions is depicted by the TMCS spatial-temporal coordination model. Subsequently, the coordinated scheduling problem is formulated as a multi-period optimization decision problem.
- 2) A lookahead rolling horizon-value function approximation (LRH-VFA) model is developed using approximate dynamic programming (ADP) for solving multiple single-period problems. Unlike the traditional methods, it does not rely on probability distributions or uncertainty sets, but learns iteratively from historical data. Thereby, the long-term impact of current decisions on future profits is considered.
- 3) The near-optimal decisions are updated by online rolling optimization. This utilizes both offline-trained approximation value function as well as short-term forecasts and real-time information. The proposed method

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can effectively utilize the dynamically updated demand changes to adjust the decisions.

The remainder of this paper is organized as follows. The operational framework and some basic models are introduced in Section II. Section III elaborates the LRH-VFA-based scheduling model and its solving procedures. Section IV presents the case study. Section V concludes the paper.

II. COORDINATED SCHEDULING MODEL OF TMCS

A. System Structure

Charging facility operators (CFO) deploy a certain number of TMCS to support FCS operations during peak charging periods. However, due to the high cost of TMCS and the uncertainty of EV charging demand. There is a need to further increase the utilization of TMCS in order to improve the profitability of CFO. In addition to assisting FCS with EV charging services, TMCS can also be deployed to specific distribution network nodes during low-utilization periods. By connecting to the distribution grid, TMCS can participate as price takers in the electricity market, engaging in energy arbitrage to generate additional profits. The coordinating strategy for these two service provisions is the key issue addressed in this paper. The operational framework of TMCS is depicted in Fig. 1 and the proposed method consists of two stages.

1) Offline training stage: The charging choices of EV users between FCS and TMCS are simulated using the multinomial logit (MNL) model to capture decision-making behavior. The spatial-temporal and error distributions of EV charging demand are generated based on historical data. An extended graph model is established to feature the dynamic characteristics of TMCS operations. By reformulating the multi-period optimization problem as a Markov Decision Process (MDP), we decouple it into successive subproblems. Piecewise linear function (PLF) is utilized to approximate the value function, and its slope is iteratively trained to embed real-world insights into the decision-making process.

2) Online operation stage: TMCS coordinated scheduling results are updated on a rolling basis based on short-term simulation results of EV charging demand and the well-trained PLFs. The iteratively converged value function minimizes the impact of EV charging demand simulation errors on CFO profits in subsequent periods. The forward rolling output of each optimization result can further improve the quality of the solution with continuously updated real-time information.

B. EV Charging Demand Generation Model

The spatial-temporal distribution of EV charging demand is mainly affected by factors such as battery characteristics, travel plans, traffic conditions, and user preferences. Consider a traffic network represented by a directed graph $\mathcal{G}(\mathcal{N}, \mathcal{A})$ with no self-loops [34]. Based on traffic flow data and market survey statistics, the origin-destination (OD) distribution of EVs and their battery parameters can be obtained. Additionally, the start/end nodes and travel paths of EVs can be obtained through OD analysis and the Floyd algorithm. Here we assume that EV users tend to choose the shortest travel route. According to the

statistics of the traffic department, the distribution of EV departure time and battery state of charge (SOC) can be obtained [13][35]. Subsequently, the Monte Carlo simulation (MCS) method is employed to determine the energy consumption patterns of EVs [32]. The travel speed of each road section is calculated by the speed-flow model given in (1), to determine the travel time of EVs and update the traffic flow of each road section.

$$\begin{cases} v_A^t = \frac{v_A^{\max}}{1 + (Q_A^t / \mathcal{R}_A)^S} \\ \mathcal{S} = a_v + b_v (Q_A^t / \mathcal{R}_A)^w \end{cases} \quad (1)$$

where, v_A^t and Q_A^t represent the average speed and actual flow of the road section at time t . In addition, outside temperature has a considerable impact on energy consumption due to increased air conditioning use by drivers, so (2a)-(2c) are adopted to account for this impact.

$$\mathcal{K}_{\text{pect}}(t) = \mathbb{K}_1 \mathcal{U}^3(t) + \mathbb{K}_2 \mathcal{U}^2(t) + \mathbb{K}_3 \mathcal{U}(t) + \mathcal{C}_1 \quad (2a)$$

$$\mathcal{K}_{\text{temp}}(t) = \mathbb{K}_4 (\mathcal{U}(t) + \mathcal{C}_2)^2 + \mathcal{C}_3 \quad (2b)$$

$$\mathcal{C}_{ei} = \begin{cases} \mathcal{K}_{\text{temp}}(t) \mathcal{C}_{ei}^N, & \text{if air conditioner is on} \\ \mathcal{C}_{ei}^N, & \text{otherwise} \end{cases} \quad (2c)$$

where, $\mathcal{K}_{\text{pect}}$ is the air conditioner opening rate; $\mathcal{K}_{\text{temp}}$ is the temperature-energy consumption proportionality coefficient; $\mathcal{C}_{ei}$ is the energy consumption per kilometer. If an EV requires charging, a set of potential charging options can be generated based on road and trip constraints along with the charging station locations. The set of charging options includes TMCS or FCS located at node m , represented by $\mathcal{S}_i$ with J elements. Consequently, the charging capacity of EVs is extended as a piecewise function, where d_i^{rc} and $\mathbb{M}_i^{m,j}$ satisfy the truncated normal distribution [13][35].

$$\mathcal{M}_i^{m,j} = \begin{cases} \eta_i \mathcal{C}_{ei} (d_i + d_i^{\text{rc}} - d_i^m), & \text{if } 0 < \eta_i \mathcal{C}_{ei} (d_i + d_i^{\text{rc}} - d_i^m) / \mathcal{M}_{ri} \leq 0.9 \\ \mathbb{M}_i^{m,j}, & \text{if } \eta_i \mathcal{C}_{ei} (d_i + d_i^{\text{rc}} - d_i^m) / \mathcal{M}_{ri} > 0.9 \end{cases} \quad (3)$$

where, $\mathcal{M}_i^{m,j}$ is the charging capacity when EV i chooses charging scheme j . EV users primarily consider charging costs and queuing time when making decisions. This paper models the cost when the user chooses charging scheme j as the sum of the charging fee and time value, as shown in (4).

$$c_i(j) = \alpha_m^j \mathcal{M}_i^{m,j} + \text{INC}_i \left(W_q^{j,t} + \mathcal{M}_i^{m,j} / \eta_{\text{dch}} P_r^j + s_c \right) / T_m \quad (4)$$

where, α_m^j is the EV charging fee per kWh; $W_q^{j,t}$ is the queuing time determined by the M/M/c/∞/∞ queue theory [36]; INC_i reflects the time value of heterogeneous users [32]. Furthermore, it is assumed that users are rational, which is a common assumption in EV charging scheduling studies [23]. And, users will weigh the utilities of different charging options, including “gains” (saving of waiting time costs) and “losses” (increasing charging fee). The discrete probability choice model, i.e., the MNL model [37], is utilized here to capture the decision process of the driver for choosing charging scheme j , which is determined in (5). At each time t , the EV charging demand of TMCS at node m can be generated by (6).

$$P_i(j) = \exp(c_i(j)) / \sum_j \exp(c_i(j)) \quad (5)$$

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$$P_m^t = \sum_i \mathcal{M}_i^{m,j}, i \in \chi_{t,m}^{\text{tmcs}} \quad (6)$$

where, $\mathcal{P}_i(j)$ is the probability that the driver chooses charging scheme j ; P_m^t is the hourly EV charging demand of TMCS at node m . Therefore, the simulation error can be obtained by fitting P_m^t with the historical charging load data.

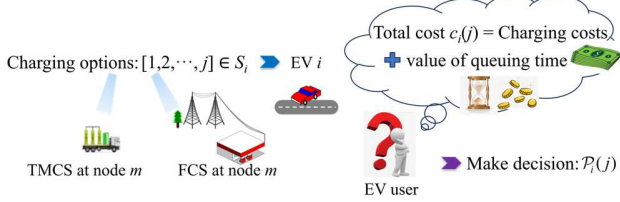


Fig. 2 The modeling process of user behavior.

The above modeling process can be graphically depicted in Fig. 2. It is noteworthy that the above model usually has sufficient accuracy in large sample simulations to generate reliable charging demand data. However, EV charging demand is affected by complex social factors such as user travel patterns, special events, and policy changes, which are difficult to simulate accurately. Therefore, how to effectively address the uncertainty of EV charging demand in TMCS scheduling optimization remains a challenge. This issue will be further analyzed in Section III. In addition, we can also adopt regret theory and cumulative prospect theory to consider the finite rational behavior of users, which is also one of our future research directions.

C. TMCS Spatial-temporal Coordination Model

As a flexible charging resource, TMCS can be deployed to provide EV charging services at appropriate locations as needed. In addition to supporting FCS, TMCS can be connected to the distribution grid at times of low utilization and participate in the electricity spot market as a price taker. During this period, TMCS is optimized to participate in energy arbitrage to earn additional profits by charging when electricity prices are low and discharging when prices are high. This dynamic strategy allows CFOs to take advantage of electricity price fluctuations to maximize revenues while maintaining the primary role of TMCS as an EV charging service.

By defining several types of virtual arcs [34][38], an extended graph model as shown in Fig. 3 is proposed to describe the scheduling state of TMCS. The virtual arcs can be categorized into two categories: transit arcs and parking arcs. Transit arcs, which comprise two nodes and the linking arc, represent feasible transit routes. Parking arcs indicate that TMCS will remain at a node for at least one-time slot.

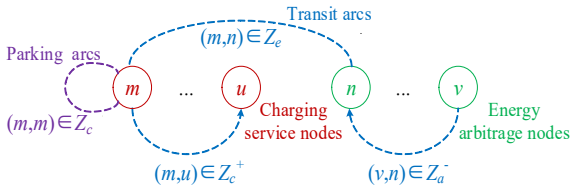


Fig. 3 The extended graph of TMCS operation

These arcs are directional and can be subdivided into three categories based on node type: charging arcs Z_c , arbitrage arcs Z_a , and exchange arcs Z_e . The positive and negative superscripts in Fig. 3 denote arcs that start or end at a node, e.g., $(m, u) \in Z_c^+$ is a charging arc that starts from node m , and (v, n)

$\in Z_a$ is an arbitrage arc that ends at node n . It can be seen that these arcs effectively capture the spatial-temporal dynamic characteristics between different service provisions. With these definitions, the spatial-temporal constraints of TMCS can be formulated as follows:

$$\sum_{(m,u) \in Z_c} \zeta_{\omega,mu}^t + \sum_{(n,v) \in Z_a} \zeta_{\omega,nv}^t + \sum_{(m,n) \in Z_e, m \neq n} \zeta_{\omega,nn}^t = 1 \quad (7a)$$

$$\sum_{(m,u) \in Z_c, m \neq u} \zeta_{\omega,mu}^t + \sum_{(m,n) \in Z_e, m \neq n} \zeta_{\omega,nn}^t \geq \zeta_{\omega,mm}^{t+1} - \zeta_{\omega,mm}^t \quad (7b)$$

$$\sum_{(n,v) \in Z_a, n \neq v} \zeta_{\omega,nv}^t + \sum_{(m,n) \in Z_e, m \neq n} \zeta_{\omega,nn}^t \geq \zeta_{\omega,nn}^{t+1} - \zeta_{\omega,nn}^t \quad (7c)$$

$$\sum_{(u,m) \in Z_c^-} \zeta_{\omega,um}^t + \sum_{(n,m) \in Z_e, n \neq m} \zeta_{\omega,nm}^t = \sum_{(m,u) \in Z_c^+} \zeta_{\omega,mu}^{t+1} + \sum_{(m,n) \in Z_e^+, m \neq n} \zeta_{\omega,nn}^{t+1} \quad (7d)$$

$$\sum_{(v,n) \in Z_a^-} \zeta_{\omega,vn}^t + \sum_{(m,n) \in Z_e, m \neq n} \zeta_{\omega,nm}^t = \sum_{(n,v) \in Z_a^+} \zeta_{\omega,nv}^{t+1} + \sum_{(n,m) \in Z_e^+, m \neq n} \zeta_{\omega,nn}^{t+1} \quad (7e)$$

$$\sum_{(n,v) \in Z_a^-} \zeta_{\omega,nv}^{t_e+1} + \sum_{(n,m) \in Z_e^+, n \neq m} \zeta_{\omega,nm}^{t_e+1} = \zeta_{\omega,nn}^{t_e} \quad (7f)$$

$$\sum_{(v,n) \in Z_a^-} \zeta_{\omega,vn}^{t_e-1} + \sum_{(m,n) \in Z_e^-, m \neq n} \zeta_{\omega,mn}^{t_e-1} = \zeta_{\omega,nn}^{t_e} \quad (7g)$$

$$\zeta_{\omega,mu}^t + \zeta_{\omega,um}^{t+1} \leq 1, m \neq u \quad (7h)$$

$$\zeta_{\omega,nv}^t + \zeta_{\omega,vn}^{t+1} \leq 1, n \neq v \quad (7i)$$

$$\zeta_{\omega,mm}^t + \zeta_{\omega,nn}^{t+1} \leq 1, m \neq n \quad (7j)$$

$$D_{mn,\omega}^t = v_{\mathcal{A}}^t \left(\sum_{(m,u) \in Z_c, m \neq u} \zeta_{\omega,mu}^t + \sum_{(n,v) \in Z_a, n \neq v} \zeta_{\omega,nv}^t + \sum_{(m,n) \in Z_e, m \neq n} \zeta_{\omega,nn}^t \right) \quad (7k)$$

where, $\zeta_{\omega,mu}^t$ is a binary variable, 1 if TMCS ω is on arc (m,u) at time t and 0 otherwise; $D_{mn,\omega}^t$ is the distance traveled by TMCS during time t . The above (7a) ensures that TMCS ω can be either on transit arcs or parking arcs. Constraints (7b) and (7c) present the relationship between transit arcs and parking arcs. Constraints (7d)-(7e) indicate that the TMCS which ends travel at a node during time t will lie on an arc starting from that node in the next time slot. (7f)-(7g) declare the initial and termination positions of each TMCS. Constraints (7h)-(7j) guarantee that TMCS cannot make an immediate round trip. Constraint (7k) is related to the energy consumption during TMCS transfers. Note that removal of (7k) has a negligible effect on the results. This is because TMCS is usually charged during low tariff periods and have relatively low transit energy consumption (less than 1.25 kWh/km) [29].

In addition, TMCSs are required to meet the following power and SOC constraints during their operation:

$$0 \leq P_{\text{ch},\omega}^t \leq \min \left(\sum_{n \in M_a} \zeta_{\omega,n}^t, I_{\text{ch},\omega}^t \right) P_{\text{ch},\omega}^{\max} \quad (8a)$$

$$0 \leq P_{\text{dch},\omega}^t \leq \min \left(\sum_{n \in M_a} \zeta_{\omega,n}^t, I_{\text{dch},\omega}^t \right) P_{\text{dch},\omega}^{\max} \quad (8b)$$

$$I_{\text{ch},\omega}^t + I_{\text{dch},\omega}^t \leq \sum_{n \in M_a} \zeta_{\omega,n}^t \quad (8c)$$

$$P_{\text{dch},\omega}^t \leq \zeta_{\omega,mm}^t P_{\text{cs},\omega}^{\max} \quad (8d)$$

$$\sum_{\omega \in \Omega_m^{c,t}} P_{\text{dch},\omega}^t \geq \max \left(P_m^t - \rho P_{\text{cs},\omega}^{\max}, 0 \right), \Omega_m^{c,t} \subseteq \Omega \quad (8e)$$

$$SOC_{\min} \leq SOC_{\omega}^t \leq SOC_{\max} \quad (8f)$$

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$$SOC_{\omega}^{t+1} = SOC_{\omega}^t - \left\{ \left(\sum_{n \in M_a} P_{dch, \omega n}^{t+1} + \sum_{m \in M_c} P_{dch, \omega m}^{t+1} \right) / \eta_{dch, \omega} - \eta_{ch, \omega} \sum_{n \in M_a} P_{ch, \omega n}^{t+1} \right\} / E_{\omega} \quad (8g)$$

where, $P_{ch, \omega n}^t$, $P_{dch, \omega n}^t$ are the charging and discharging power of TMCS ω at node n ; $I_{ch, \omega}^t$, $I_{dch, \omega}^t$ are binary variables, 1 if TMCS ω is charging or discharging at time t and 0 otherwise; $P_{cs, \omega}^{\max}$ is the maximum power that TMCS ω performs charging service, determined by the number and rated power of its chargers; ρ is the EV charging demand satisfied ratio, which reflects the charging service quality preference of CFO. Constraints (8a) and (8b) establish the feasible charging and discharging power set of TMCS ω in energy arbitrage mode. (8c) defines the charging and discharging constraints associated with the arbitrage mode. Constraints (8d)-(8e) describe the feasible discharging power set of TMCS ω in EV charging service mode. Finally, the SOC limitations are denoted in (8f) and (8g).

D. Problem Formulation

The optimization objective aims to maximize the profitability of the CFO, as illustrated below, where q^t is converted from the capacity loss per year. Note that this paper assumes that the energy consumption per kilometer and the charging/discharging efficiency of TMCS are constant. And the transit time of TMCS is rounded up, which are common but very weak assumptions in related studies [21].

$$\max_{x^t} f(x^t) = \sum_{t \in T} \sum_{\omega \in \Omega} \{ R(x^t) - C^{OM}(x^t) - C^{DEG}(x^t) \} \quad (9a)$$

$$R(x^t) = \alpha_m^{tmc} P_{dch, \omega m}^t + \lambda_n^{t,d} P_{dch, \omega n}^t - \lambda_n^{t,c} P_{ch, \omega n}^t \quad (9b)$$

$$C^{OM}(x^t) = \lambda_n^{t,c} C_{tmc} D_{mn, \omega}^t + c^{la} + c^{mt} \quad (9c)$$

$$C^{DEG}(x^t) = c^{mdc} (1 + r_0)^{\kappa(t)} \{ P_{dch, \omega m}^t + P_{dch, \omega n}^t + P_{ch, \omega n}^t + q^t \} \quad (9d)$$

where, x^t is the decision variables; R , C^{OM} and C^{DEG} denote the revenue, O&M cost, and the degradation cost, respectively.

III. LRH-VFA-BASED SOLUTION APPROACH

A. The MDP Reformulation

The above TMCS coordinated scheduling model is a MILP problem. Although the optimal solution to this problem can be obtained, it requires precise information on EV charging demand throughout the entire period. The uncertainty of EV charging demand is exogenous factor for TMCS coordinated scheduling. Therefore it is challenging to meet this requirement, making the MILP model unsuitable for real-time scheduling scenarios.

Probabilistic methods and robust optimization techniques are traditional and effective approaches for dealing with uncertainty and enhancing model robustness. The former relies on modeling uncertainties through probability distributions, while the latter focuses on ensuring solution feasibility under worst-case scenarios. However, due to the static nature of both approaches, they cannot effectively utilize dynamically updated changes in demand to adjust decisions. If we look into the online scheduling process of TMCS. Since the day is divided

into T periods, the global optimal decision from the current period to the final period needs to be determined at each stage. Additionally, the current position and battery level already incorporate the impact of prior actions on the present state, indicating that the scheduling optimization problem exhibits the Markov property. Consequently, this paper reformulates the aforementioned multi-period optimization model as an MDP and then employs dynamic programming (DP) to solve it. This approach decouples the original multi-period optimization problem into multiple sequential single-period optimization problems. These problems can be solved iteratively and the transition function facilitates the progress between successive periods [39][40].

An MDP typically consists of state variables S^t , decision variables x^t , and exogenous variables W^t . The state variables connecting the two stages are linked through a transition function. The state variables reflect the current state of the system, which is represented by (10).

$$S^t = \{ SOC_{\omega}^t, \zeta_{\omega, mu}^{t-\Delta t}, \zeta_{\omega, nv}^{t-\Delta t}, \zeta_{\omega, mn}^{t-\Delta t}, P_m^t \} \quad (10)$$

Given that the location information of the previous period affects the dispatching range of TMCS in the subsequent period, the state variables considered in this paper include $\zeta_{\omega, mu}^{t-\Delta t}$, $\zeta_{\omega, nv}^{t-\Delta t}$ and $\zeta_{\omega, mn}^{t-\Delta t}$. The TMCS scheduling process needs to determine the coordinated optimization decision based on both the current state and predictive information. In the MDP framework, the decision variables x^t are denoted as:

$$x^t = \{ P_{ch, \omega n}^t, P_{dch, \omega n}^t, P_{dch, \omega m}^t, \zeta_{\omega, mu}^t, \zeta_{\omega, nv}^t, \zeta_{\omega, mn}^t, I_{ch, \omega}^t, I_{dch, \omega}^t \} \quad (11)$$

Exogenous information is employed to model the error between the predicted and actual values of uncertain factors. As discussed in Section II, the main sources of uncertainty include EV charging demand, adjustments in charging fees, and energy arbitrage price fluctuations. The exogenous information process W^t can be defined as:

$$W^t = \{ \hat{P}_m^t, \hat{\alpha}_m^{tmc}, \hat{\lambda}_n^{t,d}, \hat{\lambda}_n^{t,c} \} \quad (12)$$

From the time perspective, W^t denotes the stochastic information obtained after the end of the previous period ($t-\Delta t$) and before the current decision x^t is made. Therefore, the evolution of the decision process is as $(W^t, S^t, x^t, W^{t+\Delta t}, S^{t+\Delta t}, x^{t+\Delta t}, \dots)$.

The transition function refers to the process by which the system transfers from the current state S^t to the next state $S^{t+\Delta t}$ based on the decision x^t and exogenous information $W^{t+\Delta t}$. Therefore, the transition function can be defined to obtain the state information of the system for the next time slot.

$$S^{t+\Delta t}(1) = S^t(1) + \frac{\Delta t}{E_{\omega}} \left\{ \left(\eta_{ch, \omega} \sum_{n \in M_a} x^t(1) - \left(\sum_{n \in M_a} x^t(2) + \sum_{m \in M_c} x^t(3) \right) / \eta_{dch, \omega} \right) \right\} \quad (13a)$$

$$S^{t+\Delta t}(2) = x^t(4) \quad (13b)$$

$$S^{t+\Delta t}(3) = x^t(5) \quad (13c)$$

$$S^{t+\Delta t}(4) = x^t(6) \quad (13d)$$

$$S^{t+\Delta t}(5) = P_m^{t+\Delta t} + W^{t+\Delta t}(1) \quad (13e)$$

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where, the numbers in brackets correspond to the order of S^t in (10), x^t in (11), and W^t in (12). In addition, the objective function (9a) can be rewritten as follows.

$$F = \max_{x^t \in X^t} E \left[\sum_{t \in T} f^t(S^t, x^t) \right] \quad (14a)$$

$$f^t(S^t, x^t) = R(S^t, x^t) - C^{\text{OM}}(S^t, x^t) - C^{\text{DEG}}(S^t, x^t) \quad (14b)$$

where, $E\{\cdot\}$ represents the expectation when considering the stochastic variable W^t . After modeling the TMCS coordinated scheduling model as an MDP, the optimal decision sequence can be obtained through the DP method by solving the Bellman equation (15).

$$V^t(S^t) = \max_{x^t \in X^t} \left\{ f^t(S^t, x^t) + \gamma E[V^{t+\Delta t}(S^{t+\Delta t}) | S^t, x^t] \right\} \quad (15)$$

where, $V^t(S^t)$ is the value function, indicating the cumulative reward of the system in state S^t over the time interval Δt .

B. The Proposed LRH-VFA Method

However, the DP algorithm faces challenges in enumerating the entire solution space due to the "curse of dimensionality" problem, making it difficult to apply in real-time scheduling of TMCS. To address this, the ADP algorithm can be employed to approximate the optimal solution of the original problem while ensuring the feasibility of online decision-making. ADP methods mainly include policy function approximation and value function approximation. For the latter, linear functions, piecewise linear functions, look-up tables and nonparametric models can be used to approximate the value function [39][40].

It is worth noting that energy arbitrage prices are usually available when making online dispatch decisions for TMCS [41]. The impact of charging fee adjustments on CFO profits will be discussed later. Therefore, this paper focuses on the effect of EV charging demand uncertainty on operator profits. Moreover, the above uncertainties will eventually be reflected as changes in the SOC of TMCS. Studies have shown that for optimization problems involving energy storage, highly accurate results can be obtained by employing PLF with convex properties to approximate the value function [42][43]. In addition, we combine the rolling horizon strategy with the ADP algorithm to capitalize on the constantly updated and successively revealed real-time information [40][44]. Unlike deep reinforcement learning (RL) methods that require extensive historical data, or MILP-based heuristics that depend on long-term forecasts, the proposed LRH-VFA method uses limited lookahead predictions. By adopting a rolling horizon framework, the method could achieve near-optimal scheduling with reduced data and computational requirements. This allows TMCS to dynamically respond to real-time charging demand fluctuations while maintaining computational efficiency. Therefore, the proposed method combines the main advantages of RL, while maintaining the efficiency and interpretability of classical optimization techniques.

The value function of the post-decision state is defined as $V_x^t(\cdot)$ to quantify the impact of the current decision on CFO's future profits, as indicated by (16a)-(16b).

$$V^t(S^t) = \max_{x^t, x^{t_1+\Delta t}, \dots, x^{t_1+(H-1)\Delta t}} \left\{ \sum_{t=t_1}^{t_1+(H-1)\Delta t} f^t(S^t, x^t) + \gamma V_x^{t_1+H\Delta t}(S_x^{t_1+H\Delta t}) \right\} \quad (16a)$$

$$V_x^{t_1+H\Delta t}(S_x^{t_1+H\Delta t}) = E[V^{t_1+H\Delta t}(S^{t_1+H\Delta t}) | S_x^{t_1+H\Delta t}] \quad (16b)$$

where, S_x^t represents the state variable after the decision; $V_x^t(\cdot)$ denotes the state of the system after a decision is executed but before any random information is received. The variable relationship and optimization process are illustrated in Fig. 4. Subsequently, the Bellman equation is rewritten as a PLF with monotonically increasing slopes.

$$V_x^{t_1+H\Delta t}(S_x^{t_1+H\Delta t}) \approx \bar{V}_x^{t_1+H\Delta t}(SOC_x^{t_1+H\Delta t}) = \sum_{\omega \in \Omega, a \in N^a} d_{a,\omega}^t r_{a,\omega}^{t_1} \quad (17)$$

where, N^a represents the total number of segments in PLF $\bar{V}_x^t(\cdot)$; SOC_x^t denotes the SOC value of TMCS after the decision; $d_{a,\omega}^t$ represents the slope for segment a of PLF. If $\bar{V}_x^t(\cdot)$ is divided into N^a segments, the following constraints (18a)-(18d) need to be satisfied.

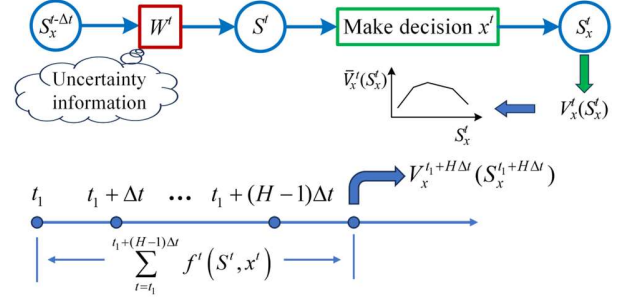


Fig. 4 The proposed LRH-VFA method

$$SOC_{\omega,x}^{t_1+H\Delta t} = \sum_{a \in N^a} r_{a,\omega}^{t_1} / E_\omega \quad (18a)$$

$$0 \leq r_{a,\omega}^{t_1} \leq (E_\omega^{\max} - E_\omega^{\min}) / N^a \quad (18b)$$

$$d_{a,\omega}^{t_1} \leq d_{a+1,\omega}^{t_1} \quad (18c)$$

$$SOC_\omega^{t_1} = SOC_\omega^{t_1+H\Delta t} + \sum_{t=t_1}^{t_1+(H-1)\Delta t} \left\{ \left(\sum_{n \in M_d} P_{\text{dch},om}^t + \sum_{m \in M_c} P_{\text{dch},om}^t \right) / \eta_{\text{dch},\omega} - \eta_{\text{ch},\omega} \sum_{n \in M_d} P_{\text{ch},om}^t \right\} / E_\omega \quad (18d)$$

where, SOC_ω^t denotes the SOC of TMCS ω before the decision x^t is executed. (18a) indicates that the TMCS energy equals the sum of the values in each segment. (18b) ensures that the values in each segment do not exceed the upper and lower limits. Constraint (18c) ensures that the slope increases monotonically with the segment number, thereby guaranteeing that PLF is a convex function. (18d) represents the change relationship of SOC before and after the decision. Furthermore, the approximate optimal decisions can be obtained by recursively solving the following equation:

$$\bar{x}^{t_1} = \arg \max_{x^t, x^{t_1+\Delta t}, \dots, x^{t_1+(H-1)\Delta t}} \left\{ \sum_{t=t_1}^{t_1+(H-1)\Delta t} f^t(S^t, x^t) + \gamma \sum_{\omega \in \Omega, a \in N^a} d_{a,\omega}^{t_1+H\Delta t} r_{a,\omega}^{t_1+H\Delta t} | S_x^{t_1+(H-1)\Delta t} \right\} \quad (19)$$

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Algorithm 1 Offline Training Process of the LRH-VFA Method

1. **Initialize:** Set the SOC and location of each TMCS, the slope of all PLFs and segments N^a , set rolling horizon value H and time step Δt ;
 2. **for** $k=1$ to maximum iteration number K **do**
 3. Generate a training scenario through MCS method;
 4. **for** $t=1$ to T **do**
 5. Observe uncertainty realizations for $[t_1, t_1+(H-1)\Delta t]$ from historical data;
 6. Obtain the decisions $x^{t_1}, \dots, x^{t_1+(H-1)\Delta t}$ by solving (20a) subject to the constraints (7a)-(8g) and (18a)-(18d);
 7. Observe the gradients and calculate the slope sample value according to (20b);
 8. Update the slopes of PLFs while retaining the convexity via (20c) and (21);
 9. **end for** (t)
 10. if $\max(|d_{a,k}^t - d_{a,k-1}^t|) \leq \varepsilon$, break;
 11. **end for** (k)
 12. **Output** the PLFs in the last iteration.
-

The optimality of the above model depends on how close the approximate value function is to the true value function, which in turn depends strongly on the slopes of the segments in the PLF. To ensure the best possible decisions, a differential iteration method is employed to train and update the slopes of the PLF segments based on historical data until the objective function converges [39][43]. It is noteworthy that after the $(k-1)$ th iteration, the approximate value function $\bar{V}_x^{t_1+H\Delta t, k-1}$ corresponding to each time period Δt are known. Thus, (19) in the k -th iteration can be rewritten as (20a), then the slope sample value of $\bar{V}_x^{t_1, k}$ is defined as (20b), and the slope of the PLF is updated as (20c).

$$\bar{x}_k^{t_1} = \arg \max_{x_k^{t_1}, x_k^{t_1+\Delta t}, \dots, x_k^{t_1+(H-1)\Delta t}} \left(\sum_{t=t_1}^{t_1+(H-1)\Delta t} f^t(S_k^t, x_k^t) \right. \quad (20a)$$

$$\left. + \gamma \sum_{\omega \in \Omega, a \in N^a} d_{a, \omega, k-1}^{t_1+H\Delta t} r_{a, \omega, k}^{t_1+H\Delta t} \middle| S_{x, k}^{t_1+(H-1)\Delta t} \right)$$

$$\hat{d}_{a, k}^{t_1}(SOC_{x, k}^{t_1}) = \partial_{x^{t_1}, x^{t_1+\Delta t}, \dots, x^{t_1+(H-1)\Delta t}} \left(\sum_{t=t_1}^{t_1+(H-1)\Delta t} f^t(S_k^t, x_k^t) \right. \quad (20b)$$

$$\left. + \gamma \sum_{\omega \in \Omega, a \in N^a} d_{a, \omega, k-1}^{t_1+H\Delta t} r_{a, \omega, k}^{t_1+H\Delta t} \right) / \partial SOC_k^{t_1}$$

$$d_{a, k}^{t_1}(SOC_{x, k}^{t_1}) = (1 - \theta_{k-1}) d_{a, k-1}^{t_1}(SOC_{x, k}^{t_1}) + \theta_{k-1} \hat{d}_{a, k}^{t_1}(SOC_{x, k}^{t_1}) \quad (20c)$$

where $d_{a, k-1}^{t_1}(SOC_{x, k}^{t_1})$ denotes the slope value of segment a in the PLF at the $(k-1)$ th iteration. It can be seen that the slope of PLF represents the impact of TMCS unit energy changes on the subsequent period profits of CFO. To ensure that the updated slopes still satisfy the monotonically increasing property, the leveling algorithm is employed to update the slope values of each segment [44].

$$d_{b, k}^{t_1} = \begin{cases} \max \{ d_{b, k-1}^{t_1}, (1 - \theta_{k-1}) d_{a, k-1}^{t_1} + \theta_{k-1} \hat{d}_{a, k}^{t_1} \}, & b > a \\ (1 - \theta_{k-1}) d_{a, k-1}^{t_1} + \theta_{k-1} \hat{d}_{a, k}^{t_1}, & b = a \\ \min \{ d_{b, k-1}^{t_1}, (1 - \theta_{k-1}) d_{a, k-1}^{t_1} + \theta_{k-1} \hat{d}_{a, k}^{t_1} \}, & b < a \end{cases} \quad (21)$$

Algorithm 2 Online Operation by Trained Slopes Using the LRH-VFA Method

1. **for** $t=1$ to T **do**
 2. Obtain the prediction result for $[t_1, t_1+(H-1)\Delta t]$ from EV charging demand generation model;
 3. Calculate the decisions $x^{t_1}, \dots, x^{t_1+(H-1)\Delta t}$ by solving (19) subject to the constraints (7a)-(8g) and (18a)-(18d);
 4. Output the scheduling result x^{t_1} ;
 5. **end for** (t)
-

The PLF slopes in the offline iterations are trained iteratively, considering the various constraints in coordinating TMCS between the two service provisions. To balance model accuracy and computational efficiency, the rolling horizon length H is set based on the reliability of short-term forecasts, while the number of piecewise linear segments N^a reflects a trade-off between approximation accuracy and computational cost. As a result, the LRH-VFA algorithm is embedded with empirical knowledge to make near-optimal decisions. Therefore, the pre-trained PLF is used for online scheduling of TMCS to optimize its operation, and the decision results are updated for each period through the rolling horizon process.

IV. CASE STUDY

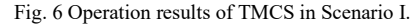
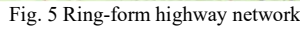
The method proposed in this paper is validated by two cases of different sizes. These cases are coded with the YALMIP toolbox in MATLAB environment and solved by Gurobi 10.0.1. The simulations are performed on a computer equipped with an i5-13500H CPU. It can be observed that the proposed method can effectively improve the utilization of TMCS and the profitability of CFO, especially in the case of low EV penetration and large gap between EV charging fees and electricity prices.

A. Test System

The ring-form highway network from [32] serves as the test system, as depicted in Fig. 5, where nodes 1-5 are the entrances and exits. Nodes 1, 2 and 4 lead to large cities, while nodes 3 and 5 connect to small cities, detailed information based on real traffic data is given in Appendix Fig. A1, Fig. A2(a), and TABLES A1-A3. The topology mirrors the current real-world application of TMCS, with these mobile charging stations serving primarily as a temporary supplement to FCS along the highway. The CFO manages 18 FCSs, the locations of which are indicated in Fig. 5, with the number of chargers at each site outlined in Appendix TABLE A4. Additionally, it is assumed that the CFO operates 4 TMCSs, each comprising a Tesla Semi and Powerpack, with 12 chargers, all within a 30-mile radius [29]. At the end of each operation day, the TMCSs return to their respective depots (depicted as red hexagons in Fig. 5). The locations of M_a are represented by pink stars in Fig. 5, and the electricity prices are determined by the time-of-use (TOU) tariffs in Henan Province, China (as illustrated in Appendix TABLE A5) [45]. Considering that the start and end of TMCS service requires a certain preparation time, Δt is set as 1h [21]. The fitting results of the EV energy consumption parameters are shown in Appendix Fig. A3. Further parameters are detailed in Appendix TABLE A6.

Assuming that the simulation error of EV charging demand follows a normal distribution $P_m^{t,c} \sim N(0, 0.1^2)$. 500 sets of offline training scenarios are generated based on the MCS method. The initial value of the slope is set as zero, and the update step size

- Scenario I: Based on weekday traffic flow, the TMCS scheduling results are compared between the EV charging service only mode (Case 1), and the coordinated scheduling mode proposed in this paper (Case 2).
- Scenario II: The above two schemes are also compared based on holiday traffic statistics [46].



The optimization results of Scenario II are presented in Appendix Fig. A4 and Fig. A5. In this scenario, the EV charging demand for TMCS significantly increases due to the elevated holiday traffic flow. Consequently, in Case 2, TMCS operates similarly to Case 1 and does not engage in energy arbitrage. It is indicated that the proposed model focuses on how to maximize TMCS utilization and operator profitability during periods of low EV charging demand. And during high charging demand periods (e.g., holidays), it still ensures that TMCSs are prioritized for EV charging services, which is the main purpose for their deployment.

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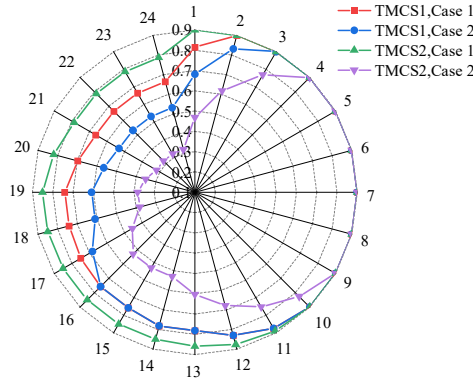


Fig. 7 SOC of TMCS in Scenario I.

To further analyze the operating states of TMCS, we define the expressions of EV charging demand satisfied ratio ρ and the TMCS capacity utilization rate δ as shown in (22) and (23), respectively. The comparison of the two scenarios is presented in TABLE I and TABLE II, where E_d^{tmc} , E_c^{tmc} , and E_a^{tmc} represent the EV charging demand of TMCS, the EV charging load met by TMCS, and the energy arbitrage discharging power, respectively. In Scenario I, Case 1, the EV charging demand is very low, and TMCS is barely profitable (¥270 during a day), with δ of only 11.02%. By engaging in energy arbitrage, the issue of TMCS idleness under low EV charging demand is addressed ($\delta=72.96\%$), resulting in much higher profitability for CFO (¥2020 during a day). In Scenario II, Case 2, due to the significant increase in charging demand, TMCS provides EV charging services only. Therefore, the profit of CFO is the same as that of Case 1. It is worth noting that we assume that c^{la} will double due to the longer service time of TMCS in Scenario II. In addition, the energy arbitrage profits of TMCS depend on the policies and subsidies of the regions where they are deployed. In some regions, injected power into the grid can be billed at the TOU tariff, such as California's rooftop solar program and the UK's Smart Export Guarantee [47][48].

$$\rho = \left(\sum_{t \in T} \sum_{\omega \in \Omega} P_{\text{dch}, \omega m}^t / \sum_{t \in T} P_m^t \right) \times 100\%, \quad \forall m \in M_c \quad (22)$$

$$\delta = \frac{\sum_{t \in T} \sum_{\omega \in \Omega} (P_{\text{dch}, \omega m}^t + P_{\text{dch}, \omega n}^t)}{\sum_{\omega \in \Omega} E_{\omega}^{\text{tmc}} (SOC_{\max} - SOC_{\min})} \times 100\%, \quad \forall m \in M_c, \quad n \in M_a \quad (23)$$

TABLE I
PROFIT COMPARISON OF TMCS

Mode	Type	R (¥10 ³)	C^{OM} (¥10 ³)	C^{DEG} (¥10 ³)	Profit (¥10 ³)
Scenario I	Case 1	2.49	1.16	1.06	0.27
	Case 2	8.33	1.13	5.18	2.02
Scenario II	Case 1	17.76	1.57	5.78	10.41
	Case 2	17.76	1.57	5.78	10.41

TABLE II
COMPARISON OF TMCS OPERATING PARAMETERS

Variable	Scenario I	Scenario II
E_d^{tmc} (kWh)	1261	12520
E_c^{tmc} (kWh)	Case 1: 992 Case 2: 766	Case 1: 9248 Case 2: 9248
E_a^{tmc} (kWh)	Case 1: 0 Case 2: 5800	Case 1: 0 Case 2: 0
ρ (%)	Case 1: 78.67 Case 2: 60.75	Case 1: 73.87 Case 2: 73.87
δ (%)	Case 1: 11.02	Case 1: 102.76

Case 2: 72.96 Case 2: 102.76

Thus, it is clear that under the weekday traffic flow of Scenario I, the coordinated scheduling model proposed in this paper increases the profitability and δ of TMCS by 6.49 times and 61.94%, respectively. In addition, the 226kW EV charging demands dropped by TMCS will be served by FCS. Another observation is that in Scenario II, 26.13% of the EV charging demand is still not served by TMCS, as shown in Fig. 8. This is due to the high charging demand at several sites simultaneously. Moreover, δ greater than 100% indicates that TMCS is charged and discharged several times during the day. Thus, the extension of FCS and TMCS can be considered comprehensively based on the values of ρ and δ in Scenario I and II.

In order to validate the performance of the LRH-VFA approach, 200 sets of test scenarios were generated by the MCS method. Using the MILP model as a benchmark, the optimized solutions of the proposed model are compared with the myopic strategy, the rolling horizon (RH) strategy, and the VFA strategy. Specifically, the myopic strategy only considers the optimal solution for a single time period, while the RH strategy updates the optimization results on a rolling basis over H time periods. The VFA strategy is the traditional ADP method, i.e., H in (16a) is set as zero. While theoretical evaluation of the solution gap of the LRH-VFA algorithm is challenging due to the complexity and stochastic nature of the problem, we empirically evaluate the algorithm through the above comparison. This provides a practical basis for assessing the solution quality of the proposed method.

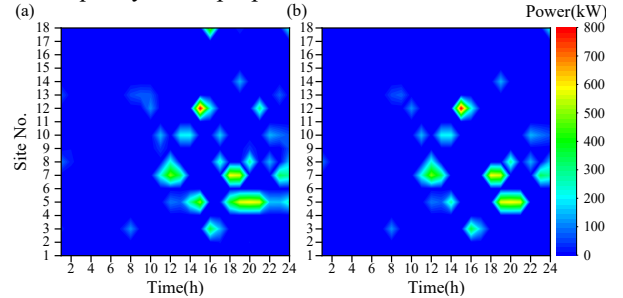


Fig. 8 Charging demand and its response of each site in Scenario II (a) EV charging demand of TMCS (b) EV charging load met by TMCS

The results obtained are shown in TABLE III. It can be observed that the myopic and RH strategies do not provide globally optimal solutions because they only focus on current or near-term optimization. Subsequent increases in EV charging demand may result in TMCS not being able to schedule in time to meet the demand. While δ rises in Scenario I through participation in grid energy arbitrage, it affects the EV charging services quality at certain times of the day. Furthermore, while the VFA approach improves coordination between TMCS service provision, the LRH-VFA approach provides a near-optimal global solution by iteratively approximating future CFO profits. This will better coordinate TMCS operations between EV charging and energy arbitrage, thereby improving charging service quality and CFO profitability. In terms of computation time, the main bottleneck comes from the need to update the spatial-temporal distribution of EV charging demand for each time period. While the LRH-VFA approach may require more computational resources and time, this time is acceptable as it is still within the operational

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limits of practical applications. For very large-scale scenarios, distributed or parallel computing can be used to reduce the solution time.

TABLE III
SCHEDULING RESULTS OF DIFFERENT METHODS

Mode	Method	Avg. profit (¥10 ³)	Avg. gap (%)	Avg. ρ (%)	Avg. δ (%)	Avg. calc. time (s)
Scenario I	Myopic	1.89	18.35	45.71	78.25	5.10
	RH	2.12	8.65	53.10	74.62	10.43
	VFA	2.18	5.82	58.62	76.88	5.71
	LRH-VFA	2.27	2.31	62.66	73.17	12.12
Scenario II	Myopic	9.00	23.44	49.82	86.51	6.85
	RH	10.55	10.32	57.10	95.02	34.06
	VFA	10.99	6.56	62.38	98.41	9.06
	LRH-VFA	11.42	2.87	67.91	107.20	39.31

In order to verify the applicability of the model, a grid-form highway network shown in Fig. 9 is applied to further validate the proposed model [49]. The network consists of 10 nodes and 18 links, the detailed data is illustrated in Appendix Fig. A2(b) and TABLE A7, A8. Based on the 2017-2023 EV stock data provided in [1] and the Perle growth curve function fitting method, it is obtained that 152,955 EVs will be traveling on this highway network in 2026. The CFO operates 20 FCSs and 18 TMCSs, and the locations of the FCSs and related nodes are shown in Fig. 9.

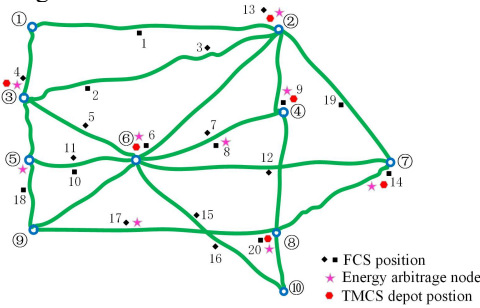


Fig. 9 Grid-form highway network

To assess the impact of prediction error on scheduling optimization, we model the EV charging demand uncertainty with a lognormal distribution and introduce artificial noise at three levels. These are denoted as base noise (BN, $P_m^c \sim \text{Log-N}(0, 0.1^2)$), medium noise (MN, $P_m^c \sim \text{Log-N}(0, 0.2^2)$), and high noise (HN, $P_m^c \sim \text{Log-N}(0, 0.3^2)$). The scheduling results for one test scenario are shown in Fig. 10 and Fig. 11, and the average results based on 500 test scenarios are shown in TABLE IV.

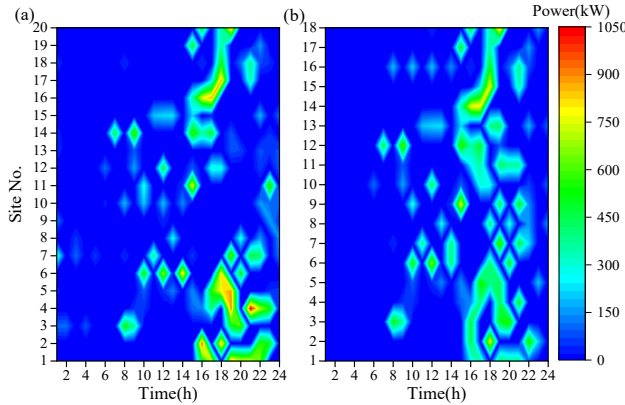


Fig. 10 EV Charging demand and its response of each site under the test scenario (a) Charging demand of TMCS (b) Charging load of each TMCS

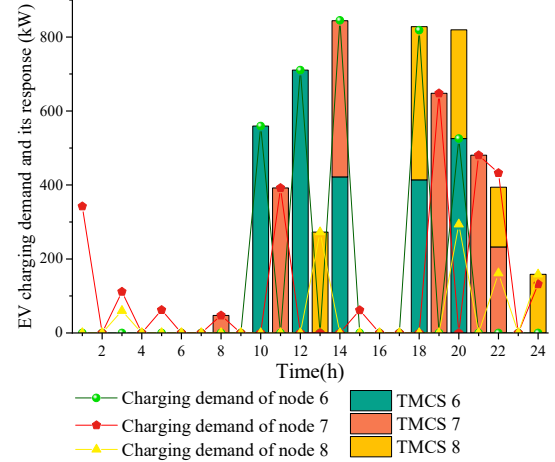


Fig. 11 Charging demand and its response at some sites in the test scenario

It is observed that the LRH-VFA method efficiently schedules the TMCS fleet to fulfill most of the charging demands. When the demand surges during peak hours, the TMCS fleet is dispatched dynamically to balance the load. For example, in Fig. 11, TMCS7 and TMCS8 are dispatched to node 6 at 14:00-15:00 and 18:00-19:00, respectively, to cope with the demand spikes. The results show that the proposed algorithm benefits from its rolling optimization mechanism and maintains a low optimization gap in the base and medium noise scenarios. It also achieves high TMCS utilization and CFO profitability. In the high noise scenarios, the increase in forecast error leads to a larger average optimization gap (7.33%) and a decrease in scheduling efficiency. This suggests that extreme uncertainty may require enhanced prediction or adaptive learning techniques.

In terms of computational efficiency, the LRH-VFA algorithm is able to make scheduling decisions within five minutes in all cases, which indicates its applicability to large-scale applications. Overall, the LRH-VFA algorithm can effectively adapt to demand fluctuations and provide near-optimal scheduling under moderate uncertainty conditions with strong robustness. Future research can further improve its adaptability through dynamic optimization and improved prediction methods.

TABLE IV
SCHEDULING RESULTS UNDER FORECAST ERRORS

Scenario	Avg. profit (¥10 ³)	Avg. gap (%)	Avg. ρ (%)	Avg. δ (%)	Avg. calc. time (s)
BN	34.52	3.23	85.75	91.67	182.07
MN	33.53	3.86	81.06	87.55	228.31
HN	30.09	7.33	73.16	78.41	281.40

In summary, it can be seen that the TMCS is a necessary complement to the FCS and helps to shift peak charging demand. Even during periods of low EV charging demand, the proposed model ensures that TMCS remains highly utilized and profitable. In addition, the model is scalable and can be adapted to regions with varying demand. TMCS can be deployed in high-demand regions and can be easily relocated as demand changes. This provides a flexible solution to meet the needs of dynamic EV charging services and energy markets.

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C. Discussions

Many factors influence the coordinated scheduling results of TMCS, including the EV growth rate, charging fees, and electricity prices.

1) EVs growth rate

Due to the uncertainty of the EV growth rate, it is essential to analyze the profits of TMCS in different years. To this end, the year order $\kappa(t)$ of the above simulation is assumed to be 1. Thus, the scheduling results of TMCS for low EV growth rate (LGR, 12.5%), medium EV growth rate (MGR, 20%), and high EV growth rate (HGR, 25%) in Case 1 and Case 2, Scenario I were studied. The profit of TMCS is shown in Fig. 12(a) and in Appendix TABLES A9-A11, where c^{la} increases annually with the discount rate r_0 . The comparison results of TMCS operating parameters under different EV growth rates are provided in Fig. 12(b)-(c) and in Appendix TABLES A12-A14.

As shown in Fig. 12(a), (c), TMCS experiences a high idle rate of δ below 40% due to low EV charging demand on weekdays during the first 4 years of operation, resulting in very low profit for Case 1. Conversely, in Case 2, only a small amount of EV charging demand (second row of Appendix TABLES A12-A14) is dropped by TMCS, and the profitability and utilization of TMCS are effectively improved by engaging in energy arbitrage.

The proposed scheduling method increases the CFO's profits by more than 133%, 112%, and 27% during the first 3-4 years of TMCS operations under LGR, MGR, and HGR, respectively (last column of Appendix TABLES A9-A11). This improvement is even greater when the EV charging demand is low. Additionally, as shown in Fig. 12(c), the values of δ are all higher than 65% in Case 2. As illustrated in Fig. 12(b), the values of ρ for Cases 1 and 2 are almost equal and above 80% at the 5th year in the LGR condition and 3rd year in the MGR and HGR conditions. It is indicated that TMCS is well-scaled to meet the EV charging load.

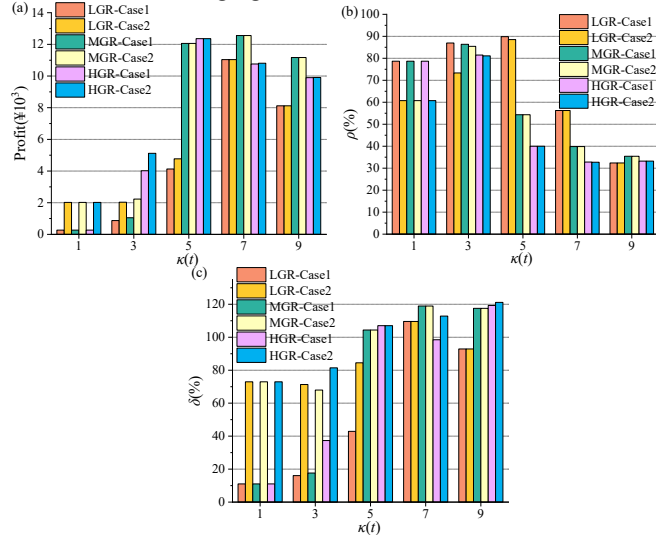


Fig. 12 Optimization results for the profit and operating parameters of TMCS. (a) Profit of TMCS (b) ρ (c) δ

As the service life increases, C^{OM} and C^{DEG} grow annually, making energy arbitrage gains less economical. At the same time, TMCS becomes more involved in charging services due to the rising EV charging demand. As indicated in Fig. 12(b)

and (c), the values of ρ are below 60% by the 7th year under LGR, and by the 5th year under MGR and HGR. Additionally, the values of δ are almost all greater than 100%. This indicates that existing TMCS deployments are no longer able to meet the growing EV charging demand, and CFO needs to deploy more equipment. Two major issues will arise if more TMCS devices are not deployed. First, TMCS cannot meet EV charging demand at multiple locations at the same time. Second, the annual growth of C^{OM} and C^{DEG} will cause the profits of CFO to decrease.

2) Pricing of EV charging services and energy arbitrage

Pricing strategies influence the distribution of traffic flows and the charging decisions of EV drivers. The discussion of parameters β_m^c , β_m^e , and β_m^a reflects the impact of price elasticity variations on TMCS scheduling. These parameters are intended to capture the impact of different pricing strategies and operator responses, thus providing practical insights for real-world applications. The EV charging fee ratio β_m^c is set as (24a). The optimization results of the coordinated scheduling strategy with different values of β_m^c are shown in Fig. 13(a) and Appendix TABLE A15. These results indicate that there is an optimal range for β_m^c . On one hand, the percentage of drivers choosing TMCS for charging increases significantly as β_m^c decreases (e.g., $\beta_m^c=1.3$), but the CFO's profit decreases. This is due to reduced revenues from EV charging services and fewer opportunities for energy arbitrage. The TMCS configuration cannot handle such high EV charging demand, resulting in a ρ of 42.43%. On the other hand, EV charging demand drops significantly when β_m^c increases, and the profits from energy arbitrage are relatively limited (e.g., $\beta_m^c=2.6$), with δ decreasing to 59.17%. This is because E_a^{tmc} is constrained by the discharging power of TMCS ($P_{deh,w}^{max}$). Determining the optimal pricing strategy for TMCS remains an important area for future research.

$$\beta_m^c = \alpha_m^{tmc} / \alpha_n^{fc} \quad (24a)$$

$$\beta_m^e = \alpha_m^{tmc} / \lambda_n^{pea} \quad (24b)$$

$$\beta_m^a = \lambda_n^{pea} / \lambda_n^{val} \quad (24c)$$

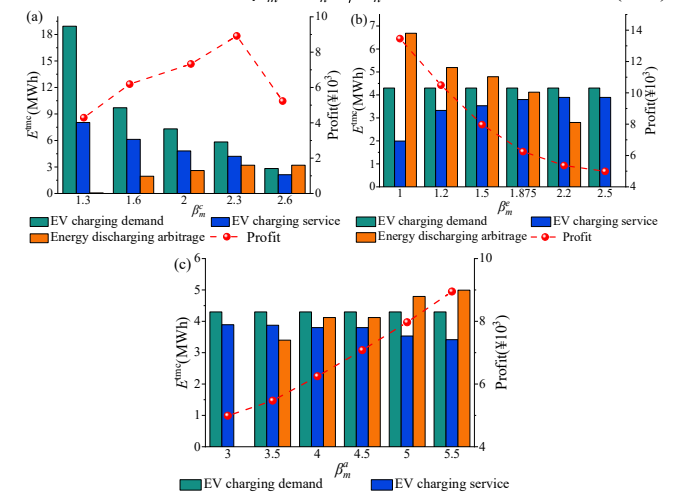


Fig. 13 Optimization results for the profit and capacity of TMCS. (a) β_m^c (b) β_m^e (c) β_m^a

Additionally, changes in electricity prices can also affect the

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scheduling results of TMCS. The arbitrage price ratio is depicted in (24b) and (24c), where λ_n^{pea} and λ_n^{val} are the peak and valley electricity prices at node n , respectively. The scheduling results of TMCS with different values of β_m^e and β_m^a are shown in Fig. 13(b), Appendix TABLE A16, Fig. 13(c), and Appendix TABLE A17. When α_m^{tmc} is constant, β_m^e decreases due to the increase in λ_n^{pea} . In this scenario, some EV charging demand is dropped to engage in energy arbitrage for greater profit (e.g., $\beta_m^e=1$), and vice versa. It is noteworthy that since EV charging demand can occur at multiple locations simultaneously, ρ does not reach to 100 even when β_m^e increases (e.g., $\beta_m^e=2.5$). However, TMCS may no longer participate in energy arbitrage if the profits become too low (e.g., $\beta_m^e=2.5$ or $\beta_m^a=3$), with δ dropping to only 43.24%. Another observation is that as β_m^a increases, E_c^{tmc} gradually decreases while E_a^{tmc} increases. Nevertheless, TMCS still meets most of the EV charging demand (e.g., $\beta_m^a=5.5$), which is attributed to the constraints on EV charging service quality. Moreover, there is a temporal complementarity between EV charging demand and energy arbitrage.

Finally, we also performed sensitivity analysis to account for stochastic price fluctuations introduced when operators adopt dynamic charging strategies or participate in intraday or balancing markets. EV charging fees (α_m^{tmc}) are modeled using a log-normal distribution, while electricity prices (λ_n^{pea} , λ_n^{val}) follow a normal distribution. Three price volatility scenarios are further considered: a low volatility (LV) scenario with $\sigma=0.1$, a medium volatility (MV) scenario with $\sigma=0.2$, and a high volatility (HV) scenario with $\sigma=0.4$. These settings allow us to simulate how changes in EV charging fees and tariffs affect the overall scheduling results, the results as shown in TABLE V.

TABLE V
SCHEDULING RESULTS UNDER PRICING VOLATILITY

Scenario	Avg. profit (¥10 ³)	Avg. gap (%)	Avg. ρ (%)	Avg. δ (%)	Avg. calc. time (s)
LV	32.45	3.61	82.11	93.20	167.03
MV	30.24	5.15	78.83	83.41	183.77
HV	27.07	11.16	68.70	79.79	225.65

As can be observed, the scheduling strategy remains robust under moderate volatility. However, when volatility increases, the performance of the model decreases due to inaccurate representation of potential demand patterns. This in turn leads to suboptimal scheduling decisions and reduced profitability. These findings suggest that integrating adaptive pricing strategies and real-time learning mechanisms may further enhance scheduling resilience under high uncertainty.

It is worth noting that the success of the model in practice depends on local energy market conditions, including electricity prices, access to the electric energy market, and EV adoption rates. Policymakers and market operators should consider these factors when promoting TMCS as a viable solution for charging infrastructure expansion. By calibrating the price parameters to reflect market characteristics, the proposed model can be adopted to various TOU tariff structures and pricing strategies. In addition, while the test scenarios have moderate computation times, larger scale systems or real-time applications may benefit from hardware upgrades (e.g., multi-

core CPUs or GPUs) and software optimizations (e.g., parallel computing). Furthermore, implementation of the model may face challenges such as the need for real-time data, necessary infrastructure investments, and integration with existing FCS and energy markets. Last but not least, differences in regulatory environments and market conditions may affect the utility of the model, thus supporting policies and market guidelines may be required.

V. CONCLUSION

In this paper, we propose a two-stage scheduling model to coordinate the operation of TMCS between EV charging services and energy arbitrage. Utilizing embedded empirical knowledge, a well-trained scheduling model based on LRH-VFA achieves a better solution than myopic strategy, RH strategy and VFA model. The proposed approach effectively improves the utilization of TMCS and the profitability of CFO compared to engaging solely in EV charging service. For instance, with a 17.92% reduction in EV charging load, the utilization of TMCS is increased by 61.94% by engaging in energy arbitrage, which leads to a 6.49-fold increase in CFO profit. This is critical to the economic operation and widespread adoption of TMCS. In addition, this strategy is more effective in increasing CFO profits when both EV penetration and TMCS utilization are relatively low. Price differences between EV charging and energy arbitrage, the number of TMCS configurations, and output power limitations can affect CFO profitability. Therefore, the allocation and pricing strategy of TMCS should be further studied to better leverage the role of TMCS in supporting FCS.

This paper does not consider competitive or cooperative relationships between multiple CFOs, and future work may include coordinated TMCS operations involving various owners. Extensions of this work also include the use of techniques such as reinforcement learning to improve model performance in more complex and nonlinear environments. In addition, the efficiency of the LRH-VFA method compared to other real-time scheduling techniques could be further explored. Future research will focus on developing adaptive mechanisms to handle unexpected changes in pricing and EV charging demand to improve forecasting accuracy. And improving parameter selection to enhance the robustness of the model under various real-world uncertainties. Another promising direction is to explore the application of TMCS in urban emergency scenarios and electricity markets such as ancillary services and renewable energy integration.

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