Leasing Business Model for Trunk Mobile Charging Stations: From the View of Operators

Kecheng He, Hongjie Jia, *Senior Member, IEEE*, Yunfei Mu, *Member, IEEE*, Xiaodan Yu, *Member, IEEE*, Yue Zhou, *Member, IEEE*, Jianzhong Wu, *Fellow, IEEE* and Xiaohong Dong, *Member, IEEE*

***Abstract*—Truck mobile charging stations (TMCS) are emerging as an effective solution to bridge the gap between supply and demand for electric vehicle (EV) charging. However, traditional business models face barriers due to high initial costs and low utilization rates, hindering operator participation. To this end, this paper introduces a bi-level optimization model for TMCS leasing to balance the TMCS operator (TMCO) and charging facility operators (CFOs). The upper-level objective maximizes the profit of TMCO, focusing on TMCS fleet size, differentiated pricing for long-term and short-term rentals, and scheduling grid energy arbitrage during idle periods. The lower level aims to maximize the profit of CFOs by determining rental quantities and durations based on leasing offers. A distributionally robust optimization (DRO) approach is employed to address the uncertainties in EV charging demand, using chance constraints with the Wasserstein distance to capture forecast errors. The probabilistic constraints are transformed into tractable linear constraints through conditional value-at-risk (CVaR) approximation. The model is solved by the genetic algorithm (GA) at the upper layer and the nested column-and-constraint generation (NC&CG) algorithm at the lower layer. Case studies show that the model effectively balances the objectives of TMCO and CFOs. With adaptive pricing and TMCS allocation strategies, the model ensures the TMCO's profitability while improving CFOs' economics.**

***Index Terms*—Truck mobile charging station, leasing business model, rental packages, distributionally robust chance constrained, profitability**

NOMENCLATURE

Sets and indexes

Ω_J^{L}	Set of TMCS
$\Omega_{j,t}^{\mathrm{c}}$	Set of TMCS of CFO j
Ω_J^{sp}	Subsets for short-term rentals
Ω_J^{lp}	Subsets for long-term rentals
$\Omega_{j,t}^{\mathrm{sp}}$	Subsets for short-term rental of CFO j
Ω_j^{lp}	Subsets for long-term rental of CFO j
t	Leasing period
th	Scheduling time
T	Planning horizon
H	Scheduling horizon
ω	Index of TMCS
r^{c}	Index of battery replacement
κ	Index of year since deployment
m, u	Operational locations for EV charging service
n, v	Operational locations for energy arbitrage
n_e	Corresponding depot location when TMCS ends service
Δ	Ambiguity set of charging demand
Ξ^2	Support set of the random variables
$\hat{\mu}$	Sample mean
ξ_1, ξ_2	Random variables
$\mathrm{W}(\cdot)$	Wasserstein distance
Π	Joint distribution of ξ_1 and ξ_2, with marginal distributions $\mathbb{P}_1$ and $\mathbb{P}_2$
$\mathbb{P}_{\mathrm{ev}}$	Potential distribution in the ambiguity set
$\boldsymbol{a}$, $\boldsymbol{b}$	Coefficient vectors
$\boldsymbol{y}$, $\boldsymbol{d}_1$	Binary variables in the first and second stages of the original problem
$\boldsymbol{d}_2$	Continuous decision variables in the second stage
$\boldsymbol{D}(\boldsymbol{y}, \beta)$	Feasible region of variable $\boldsymbol{d}$
$\mathbf{F}$, $\mathbf{G}$, $\mathbf{L}_1$-$\mathbf{L}_7$	Coefficient matrices
$\mathbf{J}_1$-$\mathbf{J}_2$, $\mathbf{S}_1$-$\mathbf{S}_3$	Coefficient matrices
$\mathbf{V}_1$-$\mathbf{V}_3$	Coefficient matrices
$\mathbb{Q}_1$-$\mathbb{Q}_7$	Constant column vectors

Parameters

$\mathcal{I}_{\omega,t}^{\mathrm{L}}$	Leasing revenue
$\mathcal{I}_{\omega,t}^{\mathrm{ch}}$	EV charging service revenue
$\mathcal{P}_{\omega,t}^{\mathrm{ea}}$	Profit of energy arbitrage
C^{IOM}	Investment, operation and maintenance (O&M) costs
$C_{\omega,t}^{\mathrm{L}}$	Leasing g cost of TMCSs
$C_{\omega,t}^{\mathrm{OM}}$	Operating cost of TMCSs
c_{ω}^{bt}	TMCS battery costs
$c_{\omega}^{\mathrm{b},f}$	TMCS battery replacement costs

This work was supported by the National Natural Science Foundation of China (52277116, U22B20105). (*Corresponding author: Hongjie Jia, Xiaodan Yu*)

K. He is with the State Key Laboratory of Intelligent Power Distribution Equipment and System, Tianjin University, Tianjin 300072, China and the School of New energy and Power Engineering, Lanzhou Jiaotong University, Lanzhou, 730070, China (e-mail: kche@tju.edu.cn).

H. Jia, Y. Mu, X. Yu and Y. Zhou are with the State Key Laboratory of Intelligent Power Distribution Equipment and System, Tianjin University, Tianjin 300072, China (e-mails: hjjia@tju.edu.cn; yunfeimu@tju.edu.cn; yuxd@tju.edu.cn; zhouyue68@tju.edu.cn).

J. Wu is with the School of Engineering, Cardiff University, CF24 3AA Cardiff, U.K. (e-mail: wuj5@cardiff.ac.uk).

X. Dong is with the State Key Laboratory of Intelligent Power Distribution Equipment and System，Hebei University of Technology, Tianjin, China (e-mail: dxh@hebut.edu.cn)

c^{pl}_{ω}	TMCS chargers and converters costs
c^{tk}_{ω}	TMCS trucks and container components
c^{dp}	Costs related to the TMCS depot
c^{mt}_{ω}	TMCS maintenance costs
η^{s}	Amortization coefficients for the TMCS system
η^{b}	Amortization coefficients for the batteries
$\eta^{\mathrm{b},f}$	Amortization coefficients for the battery replacement
η^{mt}	Amortization coefficients for the maintenance costs
η_j	Adjustment coefficient
$\eta_{\mathrm{ch},\omega}$, $\eta_{\mathrm{dch},\omega}$	Charging and discharging efficiency of TMCS
K^{b}	Service life of batteries
K^{s}	Service life of TMCS system
r_0^T	Discount rate converted to the planning horizon
N^{rc}	Total number of battery replacements
$W^{\mathrm{tmc}}_{\max}$	Maximum number of TMCSs
$W^{\mathrm{c}}_{j,t}$	Total number of TMCSs leased by CFO j
$\lambda_j^{\max}$	Upper price limit of CFO j
λ_n^{th}	Nodal price in the day-ahead energy market
λ_m^{ch}	EV charging fee per kWh
th_e	End time of TMCS scheduling
v_a	Average speed of TMCS
D^{e}_{ω}, D^{c}_{ω}	Total distance traveled during the scheduling period
$c^{H}_{\omega,j}$	Amortized self-owned cost through the scheduling horizon
c_e^{tmc}	Energy consumption per kilometer
c_{ω}^{la}	Labor cost
c^{MDC}	Life-cycle marginal degradation cost
$P^{\max}_{\mathrm{ch},\omega}$, $P^{\max}_{\mathrm{dch},\omega}$	Maximum charging and discharging power of TMCS ω
P_m^{th}	EV charging demand at node m
$P^{\max}_{\mathrm{cs},\omega}$	Maximum power of TMCS ω in EV charging service
$E^{\mathrm{tmc}}_{\omega}$	Capacity of TMCS ω
$SOC_{\max}$, $SOC_{\min}$	Maximum and minimum SOC levels of TMCS
q_{th}	Calendar degradation parameter of TMCS battery packs
γ_j^{c}	EV charging demand satisfied ratio
α, D_{ε}, φ_1, φ_2, s_l	Auxiliary variables
ε	Radius of Wasserstein ball
ρ_{ε}	Confidence level of ambiguity set
ρ_{ev}	Confidence level of chance constraint
β	Uncertain parameter related to EV charging demand

Variables

$\upsilon^{\mathrm{sp}}_{\omega,t}$	Binary variables, 1 if TMCS ω is in short-term leasing status at time t, and 0 otherwise
$\upsilon^{\mathrm{lp}}_{\omega,t}$	Binary variables, 1 if TMCS ω is in long-term leasing status at time t, and 0 otherwise
$\upsilon^{\mathrm{ea}}_{\omega,t}$	Binary variables, 1 if TMCS ω is in energy arbitrage status at time t, and 0 otherwise
λ_j^{sp}	Short-term rental package prices
λ_j^{lp}	Long-term rental package prices
W^{tmc}	Total number of TMCS
$P^{th}_{\mathrm{ch},\omega n}$, $P^{th}_{\mathrm{dch},\omega n}$	Charging and discharging power of TMCS ω at node n
$\zeta^{th}_{\omega,n}$, $\zeta^{th}_{\omega,nv}$	Binary variables, 1 if TMCS ω is on node n, or on path (n, v) at time th, and 0 otherwise
$\zeta^{th}_{\omega,mu}$, $\zeta^{th}_{\omega,mn}$	Binary variables, 1 if TMCS ω is on path (m, u), or on path (m, n) at time th, and 0 otherwise
$I^{th}_{\mathrm{ch},\omega}$	Binary variables, 1 if TMCS ω is charging at time th, and 0 otherwise

I. INTRODUCTION

Electric vehicles (EVs) have become an essential solution for reducing the carbon footprint in the transportation sector. With the widespread application of EVs, the demand for available charging facilities and convenient charging solutions is growing rapidly. The latest *Global EV Outlook 2024* report issued by the International Energy Agency (IEA) shows that EV sales continue to rise. They could 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]. The fact is that some limitations remain challenging for conventional public fixed charging stations (FCS). Firstly, the ability to deploy FCS is limited by the power available on the grid, which can take a long time to upgrade [2]. In addition, the uncertainty of EV charging demand may lead to polarization of FCS in practice. For example, some FCSs on highways may be crowded during holidays but quiet on weekdays [3]. Moreover, the return on FCS investment is often insufficient due to high upfront costs, challenges in expansion or relocation, and a lack of flexible and efficient utilization schemes [4]. As a result, FCS may not be feasible in some locations. These barriers hinder the further expansion of FCS.

Truck mobile charging station (TMCS) is expected to offer novel solutions to address the above challenges. TMCS operates similarly to the power banks for EVs instead of smartphones. It consists of a certain number of chargers and a utility-scale battery storage bank carried by truck [4]. As an effective complement, TMCS is more flexible and scalable than FCS [2][4]. It has attracted much attention in the industry. Power Sonic is a company that provides energy storage and EV charging facilities in the UK and France. The company has launched several mobile charging facilities to help users with their temporary charging needs [5]. Chinese automaker NIO announced plans to deploy 120 high-capacity TMCSs on highways in northwest and northeast China by the end of 2024 [6]. Porsche released a new mobile charging solution similar to the Tesla Megapack. The system consists of a trailer with a 2.1 MWh battery system that can charge up to 10 EVs simultaneously [7].

In recent years, research on the field of TMCS has also been very active. Relevant studies can be divided into the following three categories. The first is the integrated design of TMCS, which includes considerations such as cost [4], technical limitations [8], and battery lifespan [9]. A holistic review of the different implementations, technical routes and application perspectives of mobile charging technologies were presented [4][9]. A TMCS-based business model for the energy supply of EVs was presented using South Korea as an example [10]. The second involves the strategical deployment and planning of TMCS, specifically the selection of service locations and determination of station capacity [11][12]. The effect of integrating mobile charging into an urban EV charging network and user behaviors were simulated [13]. For the combination of FCS and TMCS, the author presented a bilevel coordinated planning framework to improve the utilization and economy of charging facilities [12]. Similarly, a coordinated planning model was proposed based on weekday and holiday traffic flows [14]. A mixed-integer linear programming (MILP) model was developed to combine TMCS with integrated energy systems, where TMCS were charged at photovoltaic power plants [15]. The third relates to the optimization of TMCS scheduling, focusing on how to utilize its flexibility to reduce operating costs[16], improve equipment utilization [17] and operator revenues [18][19]. A MILP model was established for TMCS scheduling and operator profit optimization and solved using an improved genetic algorithm [18]. 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 [20][21]. The results show that the deployment of TMCS can significantly reduce the average user waiting time [20]. Pricing mechanism and business models based on FCS and TMCS was designed [22]. As can be observed that research in this area have yielded notable results. However, few studies have fully explored the challenges associated with sustainable business models for TMCS operations [23]. This is one of the main gaps between current academic research and practical applications [9]. In particular, few studies have investigated the operation strategies of TMCS from a more comprehensive multi-stakeholder perspective. Despite the many benefits of TMCS, its current promotion faces key challenges such as high initial cost and low utilization, which hinder operators' participation [4][19].

Currently, charging facility operators typically follow two main business modes in practice. The first model is “self-build”, in which the operator funds and manages the charging stations themselves. Companies such as Tesla in the U.S., NIO and Star Charge in China [23]. This mode involves high capital expense, but grants complete control over operations and profits. Tesla, for example, has integrated its Supercharger network globally [24]. NIO’s mode emphasizes its Battery-as-a-Service (BaaS). That is, it allows customers to obtain battery swapping services on a subscription basis, thereby reducing initial vehicle costs and facilitating upgrades [25][26]. The second mode is known as “owner-operator”, where charging facilities and outsourced services are provided by owners to operators, e.g., companies such as EVgo [27]. This allows the owner to secure revenue while transferring operational risk to the operator, who faces uncertainty about charging demand and revenue. The operator, in turn, can expand its services without incurring significant upfront investments [28][29]. Despite the above-established business modes in the charging facilities sector, the commercialization of TMCS presents unique challenges. Since TMCS mainly serves as temporary support for FCS, this auxiliary role contributes to the difficulty of the widespread adoption of TMCS. TMCS suppliers often struggle with high initial costs, long payback periods, and uncertain demand patterns. These challenges can hinder the scalability and profitability of TMCS.

To address the above barriers, this paper proposes a novel TMCS leasing framework from the TMCS operator (TMCO) perspective. Existing studies [10][14][22] focus on optimizing TMCS deployment from the charging facility operators (CFOs) perspective. In contrast, the proposed model allows a dedicated TMCO to own and manage TMCSs while leasing them to CFOs. By reducing the upfront investment for CFOs and providing a stable revenue flow to TMCO, the framework reallocates financial risk and increases operational flexibility. This in turn increases the adoption and utilization of TMCS. The contributions of this work are threefold:

1) A flexible and adaptable TMCS leasing framework is proposed, in which TMCO offers both long-term and short-term leasing options to meet the various needs of CFOs. In addition, an energy arbitrage strategy is embedded during the idle periods to enhance the utilization and revenue of TMCS. The proposed framework improves resource allocation efficiency and economic feasibility.
2) Given the exogenous uncertainties associated with EV charging demand, a distributionally robust chance-constrained (DRCC) approach is applied. The model ensures the leasing framework is resilient under demand variability, leading to more reliable decision-making for both TMCO and CFOs.
3) A bi-level optimization model based on Stackelberg game theory is established to capture the interaction between TMCO and CFOs. As a leader, TMCO optimizes lease pricing and fleet size. CFOs respond as followers by adapting their leasing decisions. The pricing strategy developed facilitates coordination among operators, promotes a balanced operation for TMCO, and brings mutual economic benefits to all participants.

The remainder of this paper is organized as follows. The leasing framework is introduced in Section II. Section III elaborates the bi-level optimization model. The solving procedure is described in Section IV. Section V presents the case study. Section VI concludes the paper.

II. Framework of the Leasing Business Model

Fig. 1 depicts the framework of the TMCS leasing business model, referred to as a "provider-leaser" system, similar to a car leasing model. CFOs typically own a certain number of FCSs. Due to the rapid growth in EV charging demand and its tidal nature, CFOs may face a shortage of charging facilities in some cases. TMCO invests in and owns some TMCSs, leasing them to CFOs for EV charging services. It allows TMCO to focus on asset ownership and maintenance, while CFOs can scale up operations without significant initial capital.

Due to the dynamic nature of TMCS operations, including deployment, scheduling and on-the-go maintenance. A dedicated TMCO is necessary to ensure efficient management and smooth service delivery. TMCO can optimize asset deployment and operational efficiency through data analytics and fleet management. Meanwhile, CFOs can benefit from TMCS leasing by expanding services without taking on large investment and financial risk, focusing on charging services and operations. From a social welfare perspective, the proposed framework promotes resource-sharing and cost reduction by leveraging economies of scale, thereby improving overall social benefits.

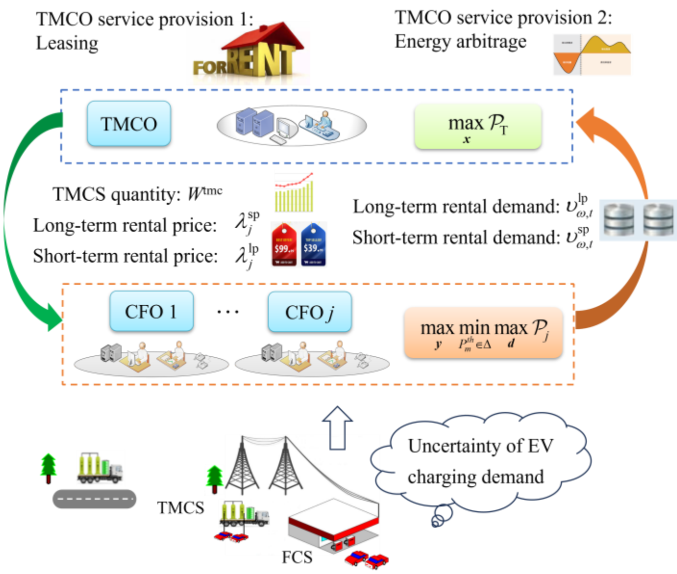

Fig. 1 The framework of the TMCS leasing business model.

The proposed leasing model is divided into long-term and short-term rental packages to address the varying needs of CFOs. The long-term rental model is intended for CFOs with relatively more stable charging demands. TMCO offers long-term rental packages with lower unit-time prices, inspiring CFOs to commit to these leases. This pricing structure ensures TMCS utilization and stable revenues for TMCO, while reducing ongoing costs for CFOs. In contrast, the short-term rental model provides flexibility for CFOs facing fluctuating or temporary demands. The two models complement each other, with long-term rentals focusing on stability and cost-effectiveness, while short-term rentals prioritize flexibility and service adaptability. In addition, the idle TMCSs can act as price takers in the electricity spot market and participate in energy arbitrage by connecting to the distribution grid for additional profits.

To enhance decision-making under uncertainty conditions, the proposed model integrates a two-stage DRCC optimization framework. This enables TMCO to manage uncertain EV charging demand and ensure high TMCS utilization while mitigating operational risks. The bilevel structure effectively captures the interaction between TMCO and CFOs, facilitating dynamic resource allocation and leasing optimization. Based on the Stackelberg game theory, the above process can be expressed as follows:

$$L=\left\{\left(J\cup\{\mathrm{TMCO}\}\right),\left\{\mathrm{X}_j\right\}_{j\in J},\left\{\mathrm{X}_\mathrm{T}\right\},\left\{\mathcal{P}_j\right\}_{j\in J},\mathcal{P}_\mathrm{T}\right\} \tag{1}$$

The game-theoretic elements of the proposed TMCS leasing model can be summarized as follows:

1) Operator set $\left(J\cup\{\mathrm{TMCO}\}\right)$, each CFO in set J act as a follower, and chooses the optimal leasing packages based on the rental prices set by the game leader TMCO.

2) CFO strategy set $\{\mathrm{X}_j\}_{j\in J}$: For the j-th CFO, its strategy set X_j includes the number of TMCS for which it decides to make a lease and its lease duration ($\upsilon_{\omega,t}^{\mathrm{sp}}$, $\upsilon_{\omega,t}^{\mathrm{lp}}$).

3) TMCO strategy set $\{\mathrm{X}_\mathrm{T}\}$: Strategy set X_T includes decisions on TMCS deployment quantities (W^{tmc}) and the pricing of long-term and short-term leases (λ_j^{lp}, λ_j^{sp}).

4) CFO utility function $\{\mathcal{P}_j\}_{j\in J}$: The utility function $\mathcal{P}_j$ of CFO j aims to maximize operational profit while meeting the required quality of service (QoS).

5) TMCO profit function $\mathcal{P}_\mathrm{T}$: The profit function $\mathcal{P}_\mathrm{T}$ of TMCO represents the difference between total revenue from leasing and energy arbitrage, and costs of investment, operations, and depreciation.

The objectives of the CFOs and TMCO are to maximize the utility and profit based on their chosen strategies respectively. A feasible solution to this game is the Stackelberg equilibrium, where the leader (TMCO) sets the optimal price taking into account the best response of the followers (CFOs). In turn, CFOs determine their optimal leasing combinations. At the equilibrium, no participant can unilaterally change their strategy to achieve a better outcome [30].

III. The Proposed Bi-level Optimization Model

A. TMCO model

The objective of TMCO is to maximize its profits during the planning horizon, as shown in (2a)-(2d).

$$\begin{cases}\max\limits_{\boldsymbol{x}} \mathcal{P}_\mathrm{T}=\sum\limits_{t\in T}\left(\mathcal{I}_{\omega,t}^{\mathrm{L}}+\upsilon_{\omega,t}^{\mathrm{ea}}\mathcal{P}_{\omega,t}^{\mathrm{ea}}\right)-C^{\mathrm{IOM}}\\ \boldsymbol{x}=\left[\lambda_j^{\mathrm{sp}},\lambda_j^{\mathrm{lp}},W^{\mathrm{tmc}},\upsilon_{\omega,t}^{\mathrm{ea}}\right]\\ \omega\in\Omega_J^{\mathrm{L}}=\left\{\Omega_J^{\mathrm{sp}}\cup\Omega_J^{\mathrm{lp}}\right\}\end{cases} \tag{2a}$$

$$\mathcal{I}_{\omega,t}^{\mathrm{L}}=\sum_{\omega\in\Omega_J^{\mathrm{sp}}}\upsilon_{\omega,t}^{\mathrm{sp}}\lambda_j^{\mathrm{sp}}+\sum_{\omega\in\Omega_J^{\mathrm{lp}}}\upsilon_{\omega,t}^{\mathrm{lp}}\lambda_j^{\mathrm{lp}} \tag{2b}$$

$$C^{\mathrm{IOM}}=\sum_{\omega}\left[\eta^{\mathrm{s}}\left(c_\omega^{\mathrm{pl}}+c_\omega^{\mathrm{tk}}\right)+\eta^{\mathrm{b}}\left(c_\omega^{\mathrm{bt}}+\eta^{\mathrm{b},f}c_\omega^{\mathrm{b},f}\right)+\eta^{\mathrm{mt}}c_\omega^{\mathrm{mt}}\right]+\eta^{\mathrm{s}}c^{\mathrm{dp}} \tag{2c}$$

$$\begin{cases}\eta^{\mathrm{s}}=r_0^T\left(1+r_0^T\right)^{K^{\mathrm{s}}}\Big/\left[\left(1+r_0^T\right)^{K^{\mathrm{s}}}-1\right]\\ \eta^{\mathrm{b}}=r_0^T\left(1+r_0^T\right)^{K^{\mathrm{b}}}\Big/\left[\left(1+r_0^T\right)^{K^{\mathrm{b}}}-1\right]\\ \eta^{\mathrm{b},f}=\sum\limits_{r^{\mathrm{c}}=1}^{N^{\mathrm{rc}}}1\Big/\left(1+r_0^T\right)^{r^{\mathrm{c}}K^{\mathrm{b}}}\\ \eta^{\mathrm{mt}}=1\Big/\left(1+r_0^T\right)^{K^{\mathrm{s}}}\end{cases} \tag{2d}$$

The first term in (2a) is the total revenue of the TMCO and the second term is the discounted value of investment and O&M costs. Items 1-3 in (2c) are the discounted values of charger, converter, truck and container component costs, battery investment and replacement costs, and maintenance costs, respectively. The set $\mathcal{S}=\{(\omega,t)\in\Omega_J^{\mathrm{sp}}\times T|\upsilon_{\omega,t}^{\mathrm{ea}}=1\}$ is defined as all (ω,t) pairs that satisfy the condition, where $\Omega_J^{\mathrm{sp}}\times T$ denotes the Cartesian product of ω and t, i.e., all possible (ω,t) combinations. Therefore, the operational constraints can be expressed as follows:

$$\upsilon_{\omega,t}^{\mathrm{sp}}+\upsilon_{\omega,t}^{\mathrm{ea}}\le 1\ \ ,\ \forall\omega\in\Omega_J^{\mathrm{sp}},\ t\in T \tag{3a}$$

$$\sum_{\omega\in\Omega_J^{\mathrm{sp}}}\upsilon_{\omega,t}^{\mathrm{sp}}+\sum_{\omega\in\Omega_J^{\mathrm{lp}}}\upsilon_{\omega,t}^{\mathrm{lp}}\le W^{\mathrm{tmc}}\le W_{\max}^{\mathrm{tmc}},\ \forall t\in T \tag{3b}$$

$$\mathcal{P}_{\omega,t}^{\mathrm{ea}}\le\lambda_j^{\mathrm{lp}}\le\lambda_j^{\mathrm{sp}}\le\lambda_j^{\max} \tag{3c}$$

$$\lambda_j^{\max}=\eta_j c_{\omega,j}^{H} \tag{3d}$$

$$\begin{aligned}\mathcal{P}_{\omega,t}^{\mathrm{ea}}=&\sum_{\omega\in\Omega_J^{\mathrm{sp}}}\sum_{th\in H}\lambda_n^{th}\left(P_{\mathrm{dch},\omega n}^{th}-P_{\mathrm{ch},\omega n}^{th}\right)-\sum_{\omega\in\Omega_J^{\mathrm{sp}}}\left(\lambda_{n_e}^{th_e}c_e^{\mathrm{tmc}}D_\omega^{\mathrm{e}}+c_\omega^{\mathrm{la}}\right)\\&-c^{\mathrm{MDC}}\left(1+r_0\right)^{\kappa}\left\{q_{th}+\sum_{\omega\in\Omega_J^{\mathrm{sp}}}\sum_{th\in H}\left(P_{\mathrm{dch},\omega n}^{th}+P_{\mathrm{ch},\omega n}^{th}\right)\right\}\end{aligned} \tag{3e}$$

$$\sum_n\zeta_{\omega,n}^{th}+\sum_{n\ne v}\zeta_{\omega,nv}^{th}=1 \tag{3f}$$

$$\sum_{n\ne v}\zeta_{\omega,nv}^{th}\ge\zeta_{\omega,n}^{th+1}-\zeta_{\omega,n}^{th} \tag{3g}$$

$$D_\omega^{\mathrm{e}}=v_a\sum_{th\in H}\sum_{n\ne v}\zeta_{\omega,nv}^{th} \tag{3h}$$

$$\zeta_{\omega,n_e}^{th_e}=1 \tag{3i}$$

$$\begin{cases}0\le P_{\mathrm{ch},\omega n}^{th}\le\min(\sum_n\zeta_{\omega,n}^{th},I_{\mathrm{ch},\omega}^{th})P_{\mathrm{ch},\omega}^{\max}\\0\le P_{\mathrm{dch},\omega n}^{th}\le\min(\sum_n\zeta_{\omega,n}^{th},I_{\mathrm{dch},\omega}^{th})P_{\mathrm{dch},\omega}^{\max}\end{cases} \tag{3j}$$

$$I_{\mathrm{ch},\omega}^{th}+I_{\mathrm{dch},\omega}^{th}\le\sum_n\zeta_{\omega,n}^{th} \tag{3k}$$

$$SOC_\omega^{th+1}=SOC_\omega^{th}-\left\{\sum_{th\in H}P_{\mathrm{dch},\omega n}^{th+1}\Big/\eta_{\mathrm{dch},\omega}-\eta_{\mathrm{ch},\omega}\sum_{th\in H}P_{\mathrm{ch},\omega n}^{th+1}\right\}\Big/E_\omega^{\mathrm{tmc}} \tag{3l}$$

$$SOC_{\min}\le SOC_\omega^{th}\le SOC_{\max} \tag{3m}$$

where, $W_{\max}^{\mathrm{tmc}}$ is determined by the TMCO budget; $\lambda_j^{\max}$ is determined by the deployment cost and leasing preference of CFO j. (3a) ensures the spatial-temporal constraint between TMCS short-term leasing and arbitrage. (3b) presents the leasing quantity limitations, while (3c)-(3d) indicate the price constraint. (3f)-(3g) guarantee the transfer constraints for TMCSs, and (3j)-(3k) define the charging and discharging constraints associated with the arbitrage mode. Finally, the SOC limitations are denoted in (3l) and (3m).

B. Two-stage DRCC model for CFOs

EV charging demand is an important exogenous variable that can have a significantly impact on the leasing strategies and scheduling arrangements of CFOs. Since historical charging load data provides certain probabilistic information. In this paper, the DRCC method is adopted to enable CFOs to make decisions by considering the worst-case probability distribution. As a result, the decision risk can be effectively reduced and the charging service quality can be ensured. The embedded chance constraints help to reduce the impact of extreme factors on the CFO's profitability, thus realizing the trade-off between decision risk and economy.

The optimization objective of CFO is shown in (4a)-(4d):

$$\begin{cases}\max\limits_{\boldsymbol{y}}\min\limits_{P_m^{th}\in\Delta}\max\limits_{\boldsymbol{d}}\mathcal{P}_j=\sum\limits_{t\in T}\left(\mathcal{I}_{\omega,t}^{\mathrm{ch}}-C_{\omega,t}^{\mathrm{L}}-C_{\omega,t}^{\mathrm{OM}}\right)\\\boldsymbol{y}=\left[\upsilon_{\omega,t}^{\mathrm{sp}},\upsilon_{\omega,t}^{\mathrm{lp}}\right]\\\boldsymbol{d}=\left[P_{\mathrm{dch},\omega m}^{th},P_{\mathrm{ch},\omega n}^{th},\zeta_{\omega,m}^{th},\zeta_{\omega,n}^{th},\zeta_{\omega,mu}^{th},\zeta_{\omega,mn}^{th},\zeta_{\omega,nv}^{th},I_{\mathrm{ch},\omega}^{th}\right]\\\omega\in\Omega_{j,t}^{\mathrm{c}}=\left\{\Omega_{j,t}^{\mathrm{sp}}\cup\Omega_j^{\mathrm{lp}}\right\}\end{cases} \tag{4a}$$

$$\mathcal{I}_{\omega,t}^{\mathrm{ch}}=\sum_{\omega\in\Omega_{j,t}^{\mathrm{c}}}\sum_{th\in H}\lambda_m^{\mathrm{ch}}P_{\mathrm{dch},\omega m}^{th} \tag{4b}$$

$$C_{\omega,t}^{\mathrm{L}}=\sum_{\omega\in\Omega_{j,t}^{\mathrm{sp}}}\upsilon_{\omega,t}^{\mathrm{sp}}\lambda_j^{\mathrm{sp}}+\sum_{\omega\in\Omega_{j,t}^{\mathrm{lp}}}\upsilon_{\omega,t}^{\mathrm{lp}}\lambda_j^{\mathrm{lp}} \tag{4c}$$

$$\begin{aligned}C_{\omega,t}^{\mathrm{OM}}=&\sum_{\omega\in\Omega_{j,t}^{\mathrm{c}}}\left\{\lambda_{n_e}^{th_e}c_e^{\mathrm{tmc}}D_\omega^{\mathrm{c}}+c_\omega^{\mathrm{la}}+\sum_{th\in H}\lambda_n^{th}P_{\mathrm{ch},\omega n}^{th}\right\}\\&+c^{\mathrm{MDC}}\left(1+r_0\right)^{\kappa}\left\{q_{th}+\sum_{\omega\in\Omega_{j,t}^{\mathrm{c}}}\sum_{th\in H}\left(P_{\mathrm{dch},\omega m}^{th}+P_{\mathrm{ch},\omega n}^{th}\right)\right\}\end{aligned} \tag{4d}$$

(4a) represents the revenue of TMCSs from the provision of EV charging services minus its leasing and operating costs. In this context, the outer "max" represents the objective of the first stage, i.e., determining its leasing strategy. The nested "min-max" formulation addresses the second-stage problem. The "min" identifies the worst-case demand scenario under a particular leasing plan. In contrast, the "max" focuses on adjusting operational strategy to ensure that all constraints are met and profits are maximized under those conditions.

In addition, the operational constraints of CFO can be expressed as follows:

$$\upsilon_{\omega,t}^{\mathrm{sp}}+\upsilon_{\omega,t}^{\mathrm{lp}}\le 1\ \ ,\ \forall\omega\in\Omega_{j,t}^{\mathrm{c}},\ t\in T \tag{5a}$$

$$\upsilon_{\omega,t}^{\mathrm{lp}}\le\upsilon_{\omega,\tau}^{\mathrm{lp}},\ \forall\omega\in\Omega_{j,t}^{\mathrm{c}},\ t\in T,\ \tau\in T \tag{5b}$$

$$\upsilon_{\omega,t}^{\mathrm{sp}}\ge\upsilon_{\omega,\tau}^{\mathrm{sp}},\ \forall\omega\in\Omega_{j,t}^{\mathrm{c}},\ t\in T,\ \tau\in T \tag{5c}$$

$$W_{j,t}^{\mathrm{c}}=\sum_{\omega\in\Omega_{j,t}^{\mathrm{c}}}\left(\upsilon_{\omega,t}^{\mathrm{sp}}+\upsilon_{\omega,t}^{\mathrm{lp}}\right) \tag{5d}$$

$$\left\lceil\max_{th\in t}\left\{P_m^{th}/P_{\mathrm{cs},\omega}^{\max}-\gamma_j^{\mathrm{c}}\right\}\right\rceil\le W_{j,t}^{\mathrm{c}}\le W^{\mathrm{tmc}} \tag{5e}$$

$$\sum_m\zeta_{\omega,m}^{th}+\sum_n\zeta_{\omega,n}^{th}+\sum_{m\ne u}\zeta_{\omega,mu}^{th}+\sum_{m\ne n}\zeta_{\omega,mn}^{th}=1 \tag{5f}$$

$$\sum_{m\ne u}\zeta_{\omega,mu}^{th}+\sum_{m\ne n}\zeta_{\omega,mn}^{t}\ge\zeta_{\omega,m}^{th+1}-\zeta_{\omega,m}^{th} \tag{5g}$$

$$\sum_{m\ne u}\zeta_{\omega,mn}^{th}\ge\zeta_{\omega,n}^{th+1}-\zeta_{\omega,n}^{th} \tag{5h}$$

$$D_\omega^{\mathrm{c}}=v_a\sum_{th\in H}\left(\sum_{m\ne u}\zeta_{\omega,mu}^{th}+\sum_{m\ne n}\zeta_{\omega,mn}^{th}\right) \tag{5i}$$

$$\zeta_{\omega,n_e}^{th_e}=1 \tag{5j}$$

$$0\le P_{\mathrm{ch},\omega n}^{th}\le\min(\sum_n\zeta_{\omega,n}^{th},I_{\mathrm{ch},\omega}^{th})P_{\mathrm{ch},\omega}^{\max} \tag{5k}$$

$$P_{\mathrm{dch},\omega m}^{th}\le\zeta_{\omega,m}^{th}P_{\mathrm{cs},\omega}^{\max} \tag{5l}$$

$$\sum_\omega P_{\mathrm{dch},\omega m}^{th}\ge\max\left(P_m^{th}-\gamma_j^{\mathrm{c}}P_{\mathrm{cs},\omega}^{\max},\ 0\right) \tag{5m}$$

$$I_{\mathrm{ch},\omega}^{th}\le\sum_n\zeta_{\omega,n}^{th} \tag{5n}$$

$$SOC_\omega^{th+1}=SOC_\omega^{th}-\left\{\sum_{th\in H}P_{\mathrm{dch},\omega n}^{th+1}\Big/\eta_{\mathrm{dch},\omega}-\eta_{\mathrm{ch},\omega}\sum_{th\in H}P_{\mathrm{ch},\omega m}^{th+1}\right\}\Big/E_\omega^{\mathrm{tmc}} \tag{5o}$$

$$SOC_{\min}\le SOC_\omega^{th}\le SOC_{\max} \tag{5p}$$

where, $P_{\mathrm{cs},\omega}^{\max}$ is mainly determined by the number and rated power of its chargers; γ_j^{c} reflects the charging service quality preference of CFO j. (5a)-(5c) establish the spatial-temporal constraints on the leasing operation, while (5d)-(5e) define the leasing quantity constraints. (5f)-(5h) guarantee the charging service and transfer constraints for TMCSs, and (5k)-(5m) set the power and QoS constraints.

It is important to note that we assume that the total CFO demand does not exceed the TMCS capacity determined by TMCO. This is to ensure efficient allocation of TMCS resources within the bilevel framework. To the extent that aggregated demand exceeds this limit, we assume that TMCO could take measures. Examples include dynamic pricing mechanisms, budget increases, or selective service reductions for less profitable CFOs. Thus balancing the leasing demand while ensuring fairness and profitability.

C. Modeling of charging demand uncertainty

Although the accurate probability distribution of P_m^{th} is not available, historical data can still provide reliable probabilistic insights that facilitate the configuration of ambiguity set. An ambiguity set is a collection of distributions at a statistical distance from a reference distribution. It provides a margin for variation in scenario probability distributions. This approach seeks to balance the economic feasibility and model robustness by constructing ambiguity sets using distance metrics. E.g., 1-norm and ∞-norm [31], χ^2 distance [32], and Wasserstein distance [33]. To address the limitations of traditional uncertainty sets (e.g., box sets or Gaussian assumptions), the Wasserstein distance is employed to construct ambiguity sets. This approach captures distributional biases based on real-world data, providing greater flexibility and robustness in dealing with uncertainty. Suppose there is a historical data set $\{\hat{\beta}^{(1)}, \hat{\beta}^{(2)}, \cdots\cdots\hat{\beta}^{(N)}\}$, where N represents the number of sample groups. The empirical distribution $\widehat{\mathbb{P}}_N$ constructed using the Dirac function is taken as an estimate of the true distribution $\mathbb{P}$.

$$\mathbb{P}_N = \sum_{l=1}^{N} \delta_{\hat{\beta}^{(l)}} \Big/ N \tag{6}$$

where, $\delta_{\hat{\beta}^{(l)}}$ is the unit point mass at $\hat{\beta}^{(l)}$. Intuitively, $\widehat{\mathbb{P}}_N$ converges to $\mathbb{P}$ as N→∞, i.e. the "distance" between $\widehat{\mathbb{P}}_N$ and $\mathbb{P}$ becomes smaller when more data is available. One of the "distances" to establish the convergence of $\widehat{\mathbb{P}}_N$ to $\mathbb{P}$ is the Wasserstein metric defined as follows:

$$\mathrm{W}\left(\mathbb{P}_1,\mathbb{P}_2\right) = \inf\left\{\int_{\Xi^2}\left\|\xi_1-\xi_2\right\|\Pi\left(d\xi_1, d\xi_2\right)\right\} \tag{7}$$

where, $\|\cdot\|_1$ denotes the norm, typically taken as the 1-norm. Therefore, we have $\mathrm{W}(\widehat{\mathbb{P}}_N,\mathbb{P}) \leqslant \varepsilon(N)$, where $\varepsilon(\cdot)$ is a monotonic function related to the sample size, decreasing to zero as N approaches infinity. Given a historical dataset with N samples, the true distribution $\mathbb{P}$ belongs to the following ambiguity set:

$$\mathbb{P}_N = \left\{\mathbb{P} \in \mathbb{P}(\Xi) : \mathrm{W}\left(\mathbb{P},\mathbb{P}_N\right) \le \varepsilon(N)\right\} \tag{8}$$

where, $\mathbb{P}_N$ is a Wasserstein ball centered at the empirical distribution $\widehat{\mathbb{P}}_N$ with a radius of $\varepsilon(N)$, and $\mathbb{P}(\Xi)$ denotes the space of all values supported by $\mathbb{P}$. The radius ε depends on the sample size (N) and the confidence level ($1-\rho_\varepsilon$) [34]:

$$\varepsilon(N) = D_\varepsilon\sqrt{\ln\left(1\big/\left(1-\rho_\varepsilon\right)\right)\big/N} \tag{9}$$

$$D_\varepsilon = \inf_{\alpha>0}\sqrt{2\left(1+\ln\left(\sum_{l=1}^{N} e^{\alpha\left\|\hat{\beta}^{(l)}-\hat{\mu}\right\|_1^2} \Big/ N\right)\right)\Big/\alpha} \tag{10}$$

The auxiliary variable α can be found by solving (10) through the bisection search method, which in turn determines D_ε and substitutes it into (9) to obtain the radius ε. Subsequently, constraint (5m) is reformulated into the DRCC form:

$$\mathbb{P}_{\mathrm{ev}}\left\{P_m^{th} - \gamma_j^{\mathrm{c}} P_{\mathrm{cs},\omega}^{\max} - \sum_{\omega} P_{\mathrm{dch},\omega m}^{th} \le 0\right\} \ge 1-\rho_{\mathrm{ev}},\ \forall \mathbb{P}_{\mathrm{ev}} \in \mathbb{P}(\Xi) \tag{11}$$

This expression can be further expressed in a compact form:

$$\inf_{\mathbb{P}_{\mathrm{ev}}\in\mathbb{P}(\Xi)} \underset{\hat{\beta}}{E}\left\{\boldsymbol{a}(\boldsymbol{d})^{\mathrm{T}}\cdot\hat{\beta} - \boldsymbol{b}(\boldsymbol{d}) \le 0\right\} \ge 1-\rho_{\mathrm{ev}} \tag{12}$$

where, $E(\cdot)$ denotes the expectation calculation. However, solving such nonlinear constraints is challenging. This paper introduces auxiliary variables φ_1, φ_2 and s_l to derive the conditional value-at-risk (CVaR) approximation for the above probabilistic constraints [35][36]:

$$\begin{cases} \varphi_1\cdot\varepsilon - \varphi_2\cdot\rho_{\mathrm{ev}} \le \sum_{l=1}^{N} s_l \Big/ N \\ s_l + \varphi_2 \le \max\left\{\boldsymbol{b}(\boldsymbol{d}) - \boldsymbol{a}(\boldsymbol{d})\hat{\beta}^{(l)}\right\} \\ \left\|\boldsymbol{a}(\boldsymbol{d})\right\|_\infty \le \varphi \\ \varphi_1 > 0, \varphi_2 \ge 0, s_l \le 0, \forall l \le N \end{cases} \tag{13}$$

The above process shows that the CVaR approximation converts the chance constraints into a set of linear constraints. Thus, a balance between computational efficiency and risk management is achieved [37][38].

IV. Solution Approach

The proposed TMCS leasing model is formulated as a bilevel programming problem where both levels include linear objective functions and constraints. The model is categorized as a MILP problem due to the presence of continuous and integer variables. Moreover, the complexity introduced by the DRCC structure makes it challenging to solve the problem with a unified optimization approach. To this end, a hybrid algorithm combining the genetic algorithm (GA) and nested column-and-constraint generation (NC&CG) is employed [39].

The upper-level problem, in which the TMCO determines the number of TMCSs and the lease prices, is solved using GA. The method is suitable as it is robust and can efficiently search for globally near-optimal solutions in non-convex and complex spaces. For low-level problems, the master problem and subproblems can be solved iteratively due to the structured decomposition approach of NC&CG. This process involves progressively adding variables and constraints to the master problem to tighten the lower bounds of the original objective function. Compared with the traditional Benders decomposition method, NC&CG reduces the number of iterations and computational overhead, ensuring more efficient convergence. The proposed hybrid approach balances computational efficiency and solution quality, making it a practical choice for addressing the complexity of the TMCS leasing model.

To facilitate explanation, the CFO model in subsection III.B. is converted into the following compact form:

$$\begin{cases} \max\limits_{\boldsymbol{y}\in \boldsymbol{Y}} \min\limits_{\beta\in\Delta} \max\limits_{\boldsymbol{d}(\boldsymbol{d}_1,\boldsymbol{d}_2)\in \boldsymbol{D}(\boldsymbol{y},\beta)} \left(\mathrm{F}^{\mathrm{T}}\boldsymbol{y}+\mathrm{G}^{\mathrm{T}}\boldsymbol{d}\right) \\ \text{s.t.}\;\; \mathrm{L}_1\boldsymbol{y}\le\mathbb{Q}_1,\;\; \mathrm{L}_2\boldsymbol{y}+\mathrm{J}_1\beta\le\mathbb{Q}_2,\;\; \mathrm{S}_1\boldsymbol{d}_1+\mathrm{L}_3\boldsymbol{y}=\mathbb{Q}_3 \\ \qquad \mathrm{S}_2\boldsymbol{d}_1+\mathrm{L}_4\boldsymbol{y}\le\mathbb{Q}_4,\;\; \mathrm{V}_1\boldsymbol{d}_2+\mathrm{S}_3\boldsymbol{d}_1+\mathrm{L}_5\boldsymbol{y}\le\mathbb{Q}_5 \\ \qquad \mathrm{V}_2\boldsymbol{d}_2+\mathrm{L}_6\boldsymbol{y}+\mathrm{J}_2\beta\le\mathbb{Q}_6,\;\; \mathrm{V}_3\boldsymbol{d}_2+\mathrm{L}_7\boldsymbol{y}=\mathbb{Q}_7 \end{cases} \tag{14}$$

The first constraint in (14) corresponds to constraints (5a)-(5c) of the original problem. The second represents the constraints of (5d)-(5e), the third corresponds to (5f), (5i)-(5j), and the fourth includes (5g)-(5h) and (5n). The fifth constraint represents (5k), (5l), while the sixth denotes (5m), and the seventh indicates constraint (5o) in the original problem.

Decomposition of (14) results in the following master problem (MP) and subproblem (SP):

$$\text{MP}\begin{cases} \max\limits_{\boldsymbol{y}}\left(\mathrm{F}^{\mathrm{T}}\boldsymbol{y}+\chi_1\right) \\ \text{s.t.}\;\; \chi_1\le\mathrm{G}^{\mathrm{T}}\boldsymbol{d}^{s_1},\;\; \mathrm{L}_1\boldsymbol{y}\le\mathbb{Q}_1 \\ \qquad \mathrm{L}_2\boldsymbol{y}+\mathrm{J}_1\beta^{s_1*}\le\mathbb{Q}_2,\;\; \mathrm{S}_1\boldsymbol{d}_1^{s_1}+\mathrm{L}_3\boldsymbol{y}=\mathbb{Q}_3 \\ \qquad \mathrm{S}_2\boldsymbol{d}_1^{s_1}+\mathrm{L}_4\boldsymbol{y}\le\mathbb{Q}_4,\;\; \mathrm{V}_1\boldsymbol{d}_2^{s_1}+\mathrm{S}_3\boldsymbol{d}_1^{s_1}+\mathrm{L}_5\boldsymbol{y}\le\mathbb{Q}_5 \\ \qquad \mathrm{V}_2\boldsymbol{d}_2^{s_1}+\mathrm{L}_6\boldsymbol{y}+\mathrm{J}_2\beta^{s_1*}\le\mathbb{Q}_6 \\ \qquad \mathrm{V}_3\boldsymbol{d}_2^{s_1}+\mathrm{L}_7\boldsymbol{y}=\mathbb{Q}_7,\;\; \forall s_1\le s_2 \end{cases} \tag{15}$$

$$\text{SP}\begin{cases} \min\limits_{\beta}\max\limits_{\boldsymbol{d}_1,\boldsymbol{d}_2}\left(\mathrm{F}^{\mathrm{T}}\boldsymbol{y}^*+\mathrm{G}^{\mathrm{T}}\boldsymbol{d}\right) \\ \text{s.t.}\;\; \mathrm{L}_2\boldsymbol{y}^*+\mathrm{J}_1\beta\le\mathbb{Q}_2 \\ \qquad \mathrm{S}_1\boldsymbol{d}_1+\mathrm{L}_3\boldsymbol{y}^*=\mathbb{Q}_3 \\ \qquad \mathrm{S}_2\boldsymbol{d}_1+\mathrm{L}_4\boldsymbol{y}^*\le\mathbb{Q}_4 \\ \qquad \mathrm{V}_1\boldsymbol{d}_2+\mathrm{S}_3\boldsymbol{d}_1+\mathrm{L}_5\boldsymbol{y}^*\le\mathbb{Q}_5 \quad \to\tau_1\ge 0 \\ \qquad \mathrm{V}_2\boldsymbol{d}_2+\mathrm{L}_6\boldsymbol{y}^*+\mathrm{J}_2\beta\le\mathbb{Q}_6 \quad \to\tau_2\ge 0 \\ \qquad \mathrm{V}_3\boldsymbol{d}_2+\mathrm{L}_7\boldsymbol{y}^*=\mathbb{Q}_7 \quad \to\tau_3 \end{cases} \tag{16}$$

where, * denotes the known quantities, while s_1 and s_2 represent the historical and current iteration counts of the outer loop, respectively; the auxiliary variable χ_1 indicates the optimal value of the second-stage objective, and τ_1, τ_2, τ_3 are dual variables associated with the relevant constraints. The outer C&CG algorithm is used to iteratively solve the MP, incorporating the scenario variable β to determine an upper bound U_{out}. The solution for the first-stage decision variable $\boldsymbol{y}$ is applied to the SP, which then provides a lower bound L_{out}. Feedback from the SP is used to update the MP, iteratively introducing new constraints and variables until the convergence criterion in (17) is met, resulting in an optimal solution.

$$\left|U_{\text{out}}-L_{\text{out}}\right|/L_{\text{out}}\le\psi \tag{17}$$

where, ψ stands for convergence gap. The SP, classified as a two-level MILP, contains binary variables $\boldsymbol{d}_1$ that do not satisfy the KKT conditions. To address this, the SP is decomposed into the master problem subset (MPS) and the subproblem subset (SPS).

The MPS reformulates the inner maximization objective into a single-level minimization problem, producing L_{in}. The SPS uses β obtained from the MPS to calculate U_{in}. Iterative updates involving $\boldsymbol{d}_1$ and the introduction of new constraints are performed until the inner loop converges (as outlined in (20)). Thus, L_{in} and L_{out} are connected and the final scenario is fed back to the MP. The solving procedures of the proposed TMCS leasing model are illustrated in Fig. 2. The iteration ends when the deviation of the operator utility function (i.e., $\mathcal{P}_{\text{T}}$, $\mathcal{P}_j$) between two iterations is less than the convergence gap.

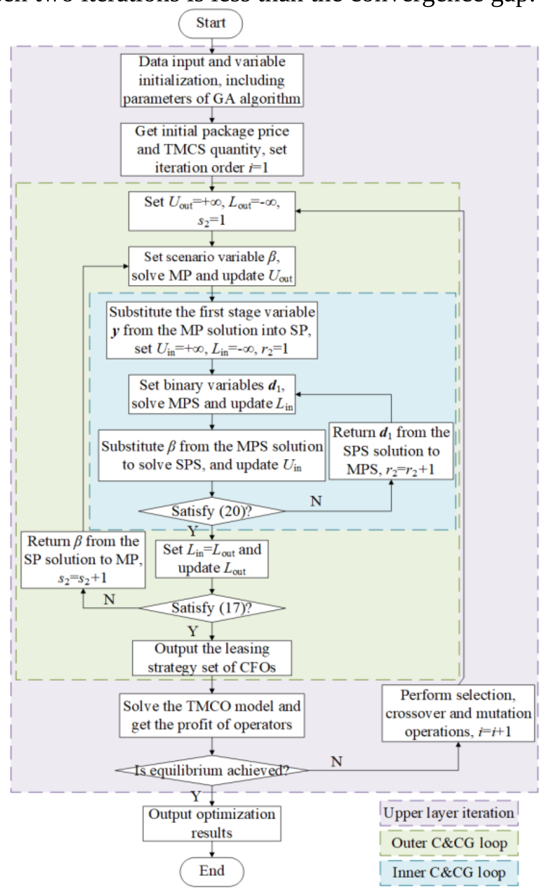

Fig. 2 Flow chart of the proposed TMCS leasing model.

$$\text{MPS}\begin{cases} \min\limits_{\beta}\left(\mathrm{F}^{\mathrm{T}}\boldsymbol{y}^*+\chi_2\right) \\ \text{s.t.}\;\; \chi_2\ge\mathrm{G}^{\mathrm{T}}\boldsymbol{d}_2^{r_1} \\ \qquad \mathrm{L}_2\boldsymbol{y}^*+\mathrm{J}_1\beta\le\mathbb{Q}_2,\;\; \mathrm{S}_1\boldsymbol{d}_1^{r_1*}+\mathrm{L}_3\boldsymbol{y}^*=\mathbb{Q}_3 \\ \qquad \mathrm{S}_2\boldsymbol{d}_1^{r_1*}+\mathrm{L}_4\boldsymbol{y}^*\le\mathbb{Q}_4,\;\; \mathrm{V}_1\boldsymbol{d}_2^{r_1}+\mathrm{S}_3\boldsymbol{d}_1^{r_1*}+\mathrm{L}_5\boldsymbol{y}^*\le\mathbb{Q}_5 \\ \qquad \mathrm{V}_2\boldsymbol{d}_2^{r_1}+\mathrm{L}_6\boldsymbol{y}^*+\mathrm{J}_2\beta\le\mathbb{Q}_6,\;\; \mathrm{V}_3\boldsymbol{d}_2^{r_1}+\mathrm{L}_7\boldsymbol{y}^*=\mathbb{Q}_7 \\ \qquad 0\le\tau_1^{r_1}\le MI_1^{r_1},\;\; \mathrm{V}_1\boldsymbol{d}_2^{r_1}+\mathrm{S}_3\boldsymbol{d}_1^{r_1*}+\mathrm{L}_5\boldsymbol{y}^*-\mathbb{Q}_5\le M\left(1-I_1^{r_1}\right) \\ \qquad 0\le\tau_2^{r_1}\le MI_2^{r_1},\;\; \mathrm{V}_2\boldsymbol{d}_2^{r_1}+\mathrm{L}_6\boldsymbol{y}^*+\mathrm{J}_2\beta-\mathbb{Q}_6\le M\left(1-I_2^{r_1}\right) \\ \qquad \mathcal{L}^{r_1}=\mathrm{G}-\mathrm{V}_1^{\mathrm{T}}\tau_1^{r_1}-\mathrm{V}_2^{\mathrm{T}}\tau_2^{r_1}-\mathrm{V}_3^{\mathrm{T}}\tau_3^{r_1} \\ \qquad 0\le\boldsymbol{d}_2^{r_1}\le MI_0^{r_1},\;\; 0\le\mathcal{L}^{r_1}\le M\left(1-I_0^{r_1}\right),\;\; \forall r_1\le r_2 \end{cases} \tag{18}$$

$$\text{SPS}\begin{cases} \max\limits_{\boldsymbol{d}_1,\boldsymbol{d}_2}\left(\mathrm{F}^{\mathrm{T}}\boldsymbol{y}^*+\mathrm{G}^{\mathrm{T}}\boldsymbol{d}\right) \\ \text{s.t.}\;\; \mathrm{S}_1\boldsymbol{d}_1+\mathrm{L}_3\boldsymbol{y}^*=\mathbb{Q}_3 \\ \qquad \mathrm{S}_2\boldsymbol{d}_1+\mathrm{L}_4\boldsymbol{y}^*\le\mathbb{Q}_4 \\ \qquad \mathrm{V}_1\boldsymbol{d}_2+\mathrm{S}_3\boldsymbol{d}_1+\mathrm{L}_5\boldsymbol{y}^*\le\mathbb{Q}_5 \\ \qquad \mathrm{V}_2\boldsymbol{d}_2+\mathrm{L}_6\boldsymbol{y}^*+\mathrm{J}_2\beta^*\le\mathbb{Q}_6 \\ \qquad \mathrm{V}_3\boldsymbol{d}_2+\mathrm{L}_7\boldsymbol{y}^*=\mathbb{Q}_7 \end{cases} \tag{19}$$

$$\left|U_{\text{in}}-L_{\text{in}}\right|/L_{\text{in}}\le\psi \tag{20}$$

where, r_1 and r_2 denote the current and historical iteration counts of the inner loop; χ_2 is an auxiliary variable representing the optimal value of the inner objective function; $\mathcal{L}^{\mathrm{u}}$ is the partial derivative of the Lagrangian function with respect to $\boldsymbol{d}_2^{\mathrm{u}}$; I_0^{u}, I_1^{u}, I_2^{u} are binary variables introduced during the linearization of the KKT complementary relaxation conditions, and M is a large positive constant.

V. Case Study

A. Test System

A ring-form highway network from [12] serves as the test system, where nodes 1-5 are the entrances and exits as depicted in Fig. 3. Nodes 1, 2 and 4 lead to large cities, while nodes 3 and 5 connect to smaller cities. The topology mirrors the current real-world application of TMCSs, with these mobile charging stations serving primarily as temporary supplements to FCS along the highway. The planning horizon is set as H for one day and T for one year. Considering that the start and end of TMCS service requires a certain preparation time, th is set as 1h [18]. The sample set is derived from the traffic statistics of the highway network in the Pearl River Delta region of China and the holiday schedule of 2023. The schedule divides the year into three typical days: weekdays, weekends, and holidays [40][41]. Eighteen FCSs along the highway belong to four independent CFOs, with locations indicated in Fig. 3. The tariffs are determined by typical time-of-use tariffs in China [42]. The population size of GA is set to 30 and the maximum number of iterations is 50. The mutation and crossover rates are chosen to be 0.2 and 0.6, respectively. Other parameters are provided in TABLE I. The experiments were performed on a computer with an Intel Core i5-13500H processor and 32 GB of RAM. The model is coded with the YALMIP toolbox in MATLAB environment and solved by Cplex 12.8.0.

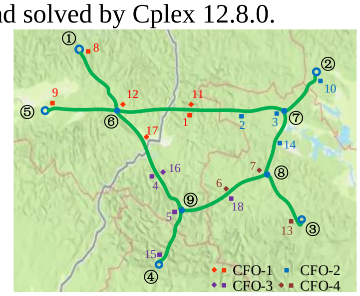

Fig. 3 The ring-form highway network and distribution of CFO operations.

TABLE I
PARAMETERS FOR SIMULATION

Variable	Value	Unit	Variable	Value	Unit
c_e^{tmc}	1.25	kwh/km	$P_{\mathrm{ch},\omega}^{\max}$	500	kW
v_a	60	km/h	$P_{\mathrm{dch},\omega}^{\max}$	300	kW
$\lambda_j^{\max}$	6	¥10^3/d	r_0^T	6	%
K^{b}	120	mth	ρ_ε	0.1	/
K^{s}	240	mth	ρ_{ev}	0.1	/
c^{MDC}	315	¥/MWh	$\eta_{\mathrm{ch},\omega}$	0.95	/
q_t	1000	kWh/d	$\eta_{\mathrm{dch},\omega}$	0.95	/
c_ω^{bt}	1000	¥/kWh	th_e	23	/
$c_\omega^{\mathrm{bt},f}$	600	¥/kWh	$SOC_{\max}$	0.95	/
c_ω^{pl}	10^5	¥/pile	$SOC_{\min}$	0.15	/
c_ω^{la}	$6*10^3$	¥/mth	N^{rc}	1	/
c_ω^{tk}	$3.5*10^5$	¥	κ	1	/

Three cases were considered to evaluate the effectiveness of the proposed approach:

- **Case 1**: A self-owned operational model is adopted by CFOs [14].
- **Case 2**: A uniform pricing scheme is applied under the proposed TMCO leasing business model.
- **Case 3** (the model in this paper): A differentiated pricing scheme is applied under the proposed TMCO leasing business model.

In addition, during periods of no charging demand, TMCSs are assigned to participate in grid energy arbitrage for additional revenue, gained by CFOs in Case 1 and by TMCO in Cases 2 and 3.

B. Simulation Results and Comparison

1) Simulation results

Fig. 4 presents the economic indicators for CFOs and TMCO. In Fig. 4a, the capacity of each TMCS is 2MW, the TMCS rental prices are converted values based on the scheduling horizon, and "CFOs" refers to the total value across all CFOs. In Fig. 4b, "C" and "$\mathcal{P}$" denote the cost and profit during the planning period, respectively, and ROI stands for the return on investment. As shown in Fig. 4a, CFO2 and CFO4 mainly choose short-term leasing, CFO1 also has 67% of demand for short-term leasing, and only CFO3 chooses long-term leasing. This highlights that most CFOs require TMCSs mainly for short-term EV charging demand, leading to low utilization during the planning period. Under the current electricity market policy, the profit gained through grid energy arbitrage is limited. As a result, Case 1 is less economical with negative ROIs (Fig. 4b), indicating that it is unprofitable for operators.

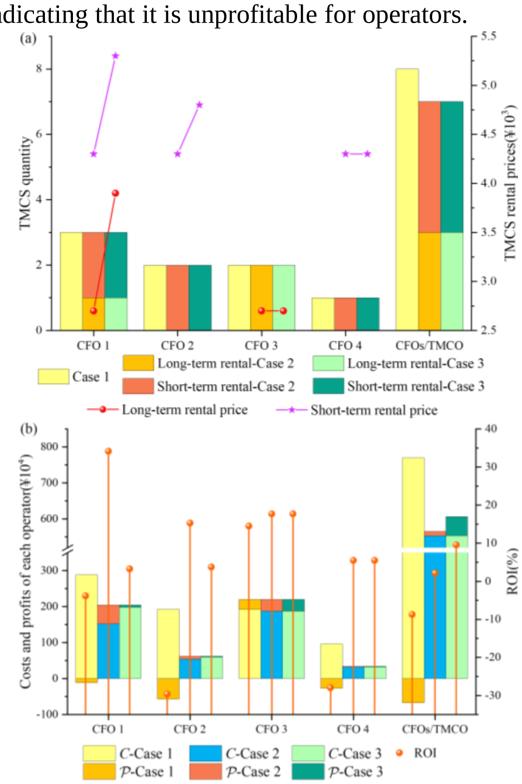

Fig. 4 Economic indicators of each operator under different cases. (a) TMCS quantity and rental prices (b) Costs and profits

In contrast, the CFO costs for Cases 2 and 3 are significantly lower. TMCO optimizes TMCS fleet size by leveraging the short-term demand differences among CFOs, thereby improving profitability. Fig. 5 illustrates the charging demand and TMCS operation states at selected sites, where positive power in Fig. 5b, 5d indicates charging and negative power indicates discharging. CFO2 would need two TMCSs on typical day 1 and one on day 2 to meet the demand, while CFO4 requires zero TMCS on typical day 1 and one on day 2. This suggests that TMCO would only need to configure two TMCSs to meet the above demand. In Case 2, the profitability of TMCO is constrained by low lease demand, particularly the long-term demand of CFO3 and the short-term demand of CFO4. However, in Case 3, TMCO takes advantage of the relatively high demand for leases from CFO1 and CFO2 to increase profits by raising lease prices. Compared to the traditional self-owned model, the proposed model resulted in a 19.27% increase in the average ROI of CFOs with guaranteed QoS, and a considerable 9.56% profit for TMCO.

It is indicated that the traditional self-owned model [14] is more suitable for CFOs with relatively stable charging demands (e.g., CFO3). This is because it eliminates recurring leasing costs and offers more predictable returns. However, this model requires significant upfront investment, making it less attractive to CFOs with limited financial capacity or variable demand profiles. In contrast, the proposed leasing model effectively addresses both long-term and short-term demands. CFOs benefit from reduced capital investment and operational risk while maintaining high QoS. TMCO optimizes TMCS utilization through resource sharing and differential pricing strategies, thereby improving profitability. In particular, the leasing model excels in managing short-term, fluctuating demand by ensuring flexibility and service continuity. Nevertheless, the adoption of differential pricing strategies may lead to imbalances, potentially driving some CFOs out of the market if lease prices are too high. Therefore, mechanisms such as fair pricing or market regulation are necessary to balance individual CFO interests and promote social welfare.

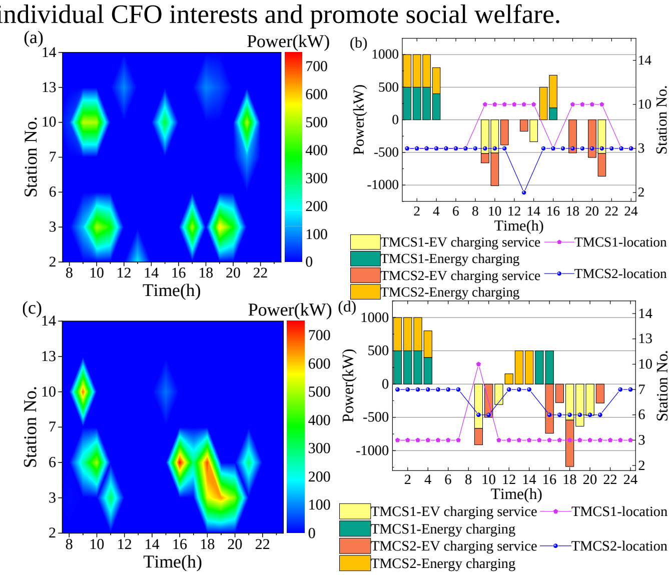

Fig. 5 Charging demand and TMCSs operation states. (a) Charging demand on day 1 (b) TMCSs operation on day 1 (c) Charging demand on day 2 (d) TMCSs operation on day 2

A key advantage of the leasing model is that TMCO is able to maximize the time-sharing reuse of TMCSs when short-term leasing needs are complementary (i.e., occur at different times). This approach reduces fleet size and investment costs, and its function is similar to time-sharing scheduling. By adapting to multiple short-term demands, the proposed model improves TMCS utilization to the benefit of both CFOs and TMCO. This dynamic change is critical to the viability of the TMCO leasing scheme. For instance, if there is no complementary short-term rental demand, the ROI of TMCO in Case 3 would fall to 3.72%. This would significantly reduce the economic viability of the leasing business model. This highlights the importance of complementary charging demand for TMCO and leads to a promising area for further research.

2) Comparative analysis

To validate the effectiveness of the proposed DRCC model, a comparative analysis was conducted using three alternative models. They are deterministic model (DM), stochastic optimization (SO), and robust optimization (RO) [43]. DM model does not account for uncertainties in charging demand. SO model assumes that the uncertainty of EV charging demand follows a Gaussian distribution. Its mean is determined by the historical charging demand with a standard deviation of 20% of the mean value. RO model employs a boxed uncertainty set that limit P_m^{th} within an interval determined by a 20% prediction error relative to the average charging demand. The schematic representation of the three uncertainty methods is depicted in Fig. 6. The SO model adopts the sample average approximation method, while the RO model identifies the worst-case scenario within the uncertainty set of P_m^{th}. TABLE II summarizes the optimization results of these methods, where "avg. QoS rate" refers to the average percentage by which each CFO meets its charging needs.

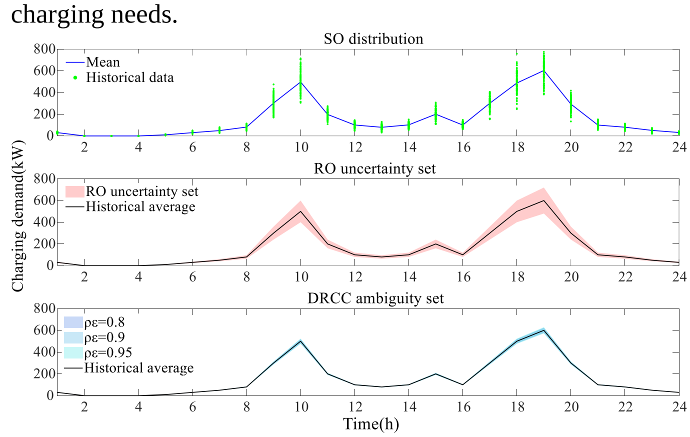

Fig. 6 Schematic visualization of each uncertainty model.

DM model achieves the minimum number of leases as well as profit maximization for CFOs and TMCO under deterministic conditions. Nevertheless, it lacks robustness and struggles to maintain expected profits or service quality during demand fluctuations. Among the uncertainty models, the SO model is the most aggressive and achieves the highest CFO profits. However, its lower lease prices and higher TMCS quantity than DRCC result in lower TMCO profits. The effectiveness of SO model is highly dependent on the number and distribution of scenarios. While a larger, more realistic set of scenarios can improve accuracy, it significantly increases computational expense, as shown in Fig. 7. RO model is the most conservative, focusing on worst-case realizations. This approach ensures the highest rental quantity and service quality but results in lower operator profits due to its high costs and ignoring probabilistic information. In some cases, the TMCO may experience negative profits, indicating infeasibility.

TABLE II
OPTIMIZATION RESULTS OF DIFFERENT MODELS

Model	Short-term lease quality	Long-term lease quality	Total quality	Avg. short-term price (¥10^3)	Avg. long-term price (¥10^3)	Avg. ROI of CFO (%)	ROI of TMCO (%)	Avg. QoS rate (%)
DM	4	3	6	4.3	3	10.62	13.06	68.12
SO	5	4	8	4.7	2.9	8.95	6.91	78.05
RO	7	4	10	5.1	3.3	2.31	-7.85	86.61
DRCC	5	3	7	4.9	3.1	7.56	9.57	72.26

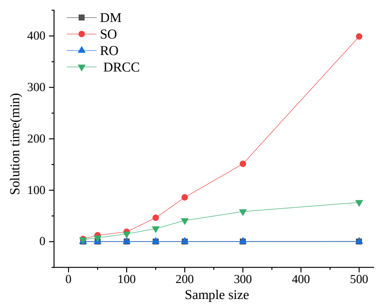

Fig. 7 Solution time of different models.

The proposed DRCC model strikes a balance between SO and RO. It adapts to data conditions by adjusting sample size and constructing uncertainty sets using the Wasserstein distance. By fine-tuning parameters like ε and ρ_{ev}, DRCC ensures QoS, accommodates demand fluctuations, and maintains balanced profits for CFOs and TMCO. Fig. 8 illustrates how the Wasserstein ball radius varies with sample size and confidence level. With fewer samples, the ambiguity set expands to account for distributional uncertainty, making DRCC behave similarly to RO model at high confidence levels (e.g., 0.99). As the sample size grows, the ambiguity set shrinks and DRCC performs closer to SO, which is optimized based on historical data to improve profitability. Overall, the DRCC model offers a flexible and efficient approach that balances cost, profit, and reliability. It outperforms SO and RO in terms of adaptability and computational efficiency, especially for large datasets. It achieves this while improving charging service quality and optimizing TMCS utilization. Future research could perform out-of-sample validation by testing different probability distributions and ambiguity set configurations. This will help to further understand the generalization ability of the model under different uncertainty conditions.

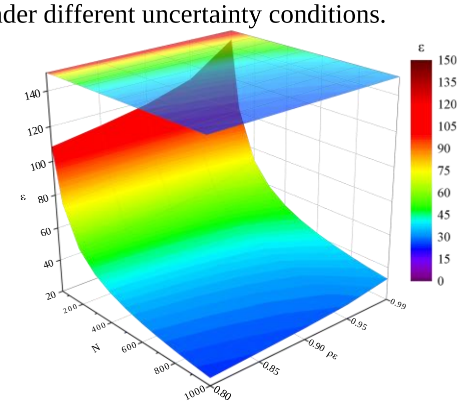

Fig. 8 Relationship between N, ρ_ε and ε.

C. Discussions

Key parameters such as ρ_{ev} and ρ_ε have a notable impact on both TMCO and CFOs decisions. As a long-term uncertainty factor in different planning cycles, the growth of the EV stock can further influence operator's strategies.

Fig. 9a presents the impact of ρ_{ev} on the optimization results of the leasing business model. Lower values of ρ_{ev} (e.g., ρ_{ev}=0.05) lead CFOs to increase short-term and long-term rentals to cope with higher uncertainty. This leads to higher TMCS allocation costs and lower TMCO ROI. Conversely, a higher value of ρ_{ev} (e.g., ρ_{ev}=0.2) drive CFOs to reduce their rental demands, allowing TMCO to reduce TMCS deployment. This increases the TMCO ROI at the expense of QoS, which drops to 62.81%.

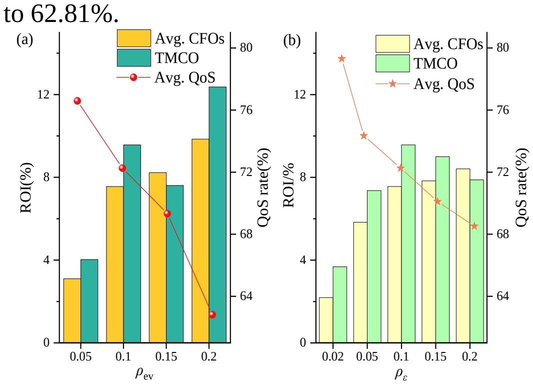

Fig. 9 Optimization results for different parameter values. (a) ρ_{ev} (b) ρ_ε

Similarly, Fig. 9b reveals the role of ρ_ε, which controls the size of the Wasserstein uncertainty set and thus affects leasing strategy and TMCS deployment. Lower values of ρ_ε (e.g., ρ_ε=0.02) result in CFOs increasing short-term leasing, which leads to higher TMCS deployment costs and lower TMCO ROI. As ρ_ε increases (e.g., ρ_ε=0.1), the leasing decisions stabilize, leading to higher TMCO and CFOs profitability. However, further increases in ρ_ε (e.g., ρ_ε=0.2) reduce the demand of CFOs and slightly increase their ROI, while decreasing TMCO profitability and QoS. These results highlight the trade-off between uncertainty managing, TMCS deployment costs, and service quality. And TMCO needs to optimize profitability while maintaining service quality and market viability.

Fig. 10 illustrates the impact of long-term uncertainty on leasing demand for each planning year. In this case, the growth in EV charging demand is based on the 2017-2023 EV stock data provided in [1] and obtained by fitting the Pearl growth curve function. The number of TMCS increases significantly from 7 at κ=1 to 68 at κ=7, indicating that the model is able to capture this type of uncertainty. Due to the effective balance between short-term and long-term leasing strategies and the efficient allocation of TMCSs, the TMCO ROI initially increases, peaking at 15.65% at κ=5. The ROI then declines slightly due to the continued increase in TMCS configuration costs, battery replacement costs, and O&M costs. Meanwhile, these results highlight the importance of long-term leasing and time-sharing reuse for TMCO profitability. While short-term leasing dominates in the early years, long-term leasing grows more rapidly as κ increases. In addition, time-sharing reuse of short-term rental demand plays an essential role in optimizing TMCS deployment and reducing additional costs.

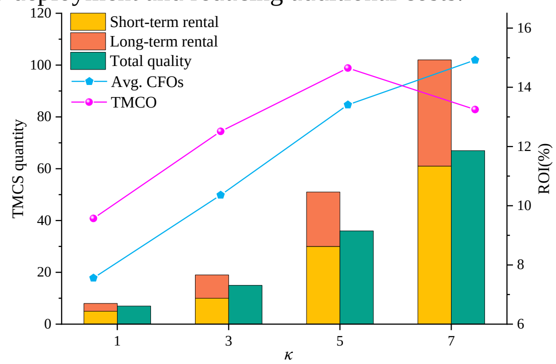

Fig. 10 Optimization results for different values of κ.

It is worth noting that while electricity price fluctuations affect grid arbitrage profitability, the impact on overall optimization results remains limited. This is because grid arbitrage profits are generally lower than TMCS leasing revenues, making it less influential in TMCO's strategic decisions. In addition, CFOs are required to maintain certain charging service rates to ensure that service levels remain relatively stable even if electricity prices fluctuate. Therefore, while electricity prices can affect arbitrage opportunities, they do not significantly change the leasing optimization results.

VI. CONCLUSION

This paper presents a bi-level optimization framework for TMCS leasing, where the TMCO acts as the leader responsible for equipment investment and operations. TMCO offers flexible long-term and short-term leasing options to CFOs and schedules TMCSs for grid energy arbitrage during idle periods to improve utilization and revenue. Case study results demonstrate that the proposed model effectively balances various demands. The uncertainty associated with charging demand is also taken into account, which reduces the decision-making risk. CFOs mainly take short-term leases to meet the peak demand, while TMCO benefits from long-term leases, differential pricing strategies, and complementary short-term leases. Compared to the traditional self-owned model, the proposed model increases the average ROI of CFOs by 19.27% with assured QoS and generates a decent 9.56% profit for TMCO. The bilevel structure of the model ensures strategic interaction between TMCO and CFOs, optimizing leasing decisions and resource allocation. This framework provides a sustainable and economically viable solution for TMCS deployment, ensuring profitability and co-benefits for all parties involved.

In addition, our model assumes homogeneous CFO behavior, i.e., all CFOs are presumed to react similarly to pricing and service conditions. The model also does not account for potential cooperative or competitive interactions among CFOs or scenarios involving multiple TMCOs. These assumptions simplify the model, but we recognize that they may not fully capture the complexity of real-world market dynamics. Future research should address these aspects to further optimize stakeholder outcomes and explore scalable hybrid algorithms. Examples include the development of hybrid algorithms that combine NC&CG with advanced decomposition techniques to improve computational performance. Parallelization strategies for GA will also be explored to leverage its inherent parallelism and reduce execution time. Furthermore, scalable meta-heuristics that combine heuristic exploration with deterministic methods will be investigated to achieve faster convergence in larger problem instances. These improvements are intended to enhance the adaptability and scalability of the proposed methods for more extensive real-world applications.

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Kecheng He (Student Member, IEEE) is currently pursuing the Ph.D. degree in Electrical Engineering at Tianjin University, Tianjin, China. From 2024 to 2025, he was a Visiting Ph.D. Student at the School of Engineering, Cardiff University, Cardiff, U.K. He is also a Lecturer with Lanzhou Jiaotong University, Lanzhou, China. His research interests include electric vehicle-to-grid, modelling and optimization of power systems.

Hongjie Jia (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Tianjin University, Tianjin, China, in 1996, 1998, and 2001, respectively, where he is a Professor. His research interests include power system stability analysis and control, distribution network planning, renewable energy integration, and smart grids.

Yunfei Mu (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Tianjin University, Tianjin, China, in 2007, 2009, and 2012, respectively, where he is currently a Professor. From 2010 to 2011, he was a Research Assistant with the School of Engineering, Cardiff University, Cardiff, U.K. His research interests include power system stability analysis and control, demand response, and integrated energy systems.

Xiaodan Yu (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Tianjin University, Tianjin, China, in 1996, 1998, and 2013, respectively, where she is currently a Professor. Her research interests include power system stability analysis, nonlinear dynamic circuit, and the optimal operation of power system.

Yue Zhou (Member, IEEE) received the B.Eng. and Ph.D. degrees in electrical engineering from Tianjin University, Tianjin, China, in 2011 and 2016, respectively. From 2017 to 2020, he was a Postdoctoral Research Associate with the School of Engineering, Cardiff University, Cardiff, U.K. Since April 2020, he has been a Lecturer of cyber physical systems with the School of Engineering, Cardiff University, Wales, U.K. He is currently a Professor at Tianjin University. His research interests include cyber physical energy systems, specifically including demand side response, peer-to-peer energy trading, distributed ledger technology, and smart local energy systems.

Jianzhong Wu (Fellow, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from Tianjin University, China, in 1999, 2002, and 2004, respectively. From 2004 to 2006, he was with Tianjin University, where he was an Associate Professor. From 2006 to 2008, he was a Research Fellow with the University of Manchester, Manchester, U.K. He is a Professor of Multi-Vector Energy Systems and the Head of the School of Engineering, Cardiff University, U.K. His research interests include integrated multi-energy infrastructure and smart grid. He is Co-Editor-in-Chief of Applied Energy and the Co-Director of U.K. Energy Research Centre and EPSRC Supergen Energy Networks Hub.

Xiaohong Dong (Member, IEEE) received the M.S. and Ph.D. degrees in electrical engineering from Tianjin University, Tianjin, China, in 2013 and 2018, respectively. She is currently a Lecturer with the State Key Laboratory of Intelligent Power Distribution Equipment and System， Hebei University of Technology. Her research interests include electric vehicle charging infrastructure planning and power system stability analysis.