

Prescriptive Decision-making in Nested Bi-level MO-IGDT Model for Integrating Parking Lots into Local Multi-carrier Energy System

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Abstract—Electrical parking lots (EPLs) play a vital role in the current energy system to achieve the decarbonization goal. This paper proposes a novel structure for integrating EPLs into a multi-carrier energy system (MCES) using a Stackelberg game theory approach. The bi-level optimization is used to model the Stackelberg game. Within this bi-level optimization model, the MCES operator minimizes the MCES cost by participating in the upstream energy market at the upper level, and the EPL operators maximize their profits by participating in the local energy market between the MCES operator and themselves at the lower level. At the upper level, the MCES operator faces uncertainties in the wind and PV systems. The bi-level multi-objective information gap decision theory (MO-IGDT) is employed to address uncertainties at the upper level of the Stackelberg game problem, resulting in a nested bi-level optimization model. The nested bi-level optimization problem is converted into a mixed-integer linear programming (MILP) optimization problem using Karush–Kuhn–Tucker (KKT) conditions. The main research assumptions pertain to EPLs’ privacy and the KKT-based approach. The results demonstrate that increasing the incentive/penalty price for self-sufficiency programs from 0.0 \$/% to 0.2 \$/%, with a 50% self-sufficiency target, can reduce MCES operation costs by 10.19%.

Index Terms—Bi-level optimization, electrical parking lots, information gap decision theory (MO-IGDT), multi-carrier energy system (MCES), multi-objective optimization.

NOMENCLATURE

A. Acronyms

ADMM	Alternating direction method of multipliers.
CHP	Combined heat and power.
DERs	Distributed energy resources.
DRP	Demand response program.

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EPLs	Electrical parking lots.
EVs	Electric vehicles.
KKT	Karush–kuhn–tucker.
MCES	Multi-carrier energy system.
MILP	Mixed-integer linear programming.
MO-IGDT	Multi-objective information gap decision theory.
PV	Photovoltaic.
SOC	State of charge.

B. Indices

t, N_t	Index and set of time intervals.
p, N_p	Index and set of parking lots.
i, N_i	Index and set of dual variables.

C. Parameters

$a_{t,p}^{\text{MT,EPL}}$	Cost coefficient of micro-turbine unit (\$/kWh).
$\bar{E}^{\text{TS}}, \underline{E}^{\text{TS}}$	Maximum/Minimum heat storage level of heat storage (kWh).
EL_t, TL_t	Electricity/Heat demand before DRP (kW).
GL_t	Gas demand (kW).
$\bar{H}^{\text{BO}}, \underline{H}^{\text{BO}}$	Maximum/Minimum heat of boiler unit (kW).
$\bar{H}^{\text{CH/DCH,TS}}$	Maximum charge/discharge rate of heat storage (kW).
$H_{\text{A/B/C/D}}^{\text{CHP}}$	Heat constants of CHP unit (kW).
$\bar{H}^{\text{H,Buy/Sell}}$	Maximum buying/selling heat from/to the grid (kW).
$\bar{G}^{\text{G,Buy}}$	Maximum buying gas from the grid (kW).
$\bar{P}^{\text{E,Buy/Sell}}$	Maximum buying/selling electricity from/to the grid (kW).
$P_{\text{A/B/C/D}}^{\text{CHP}}$	Power constants of CHP unit (kW).
P_t^{PV}	Output power of PV system (kW).
$P_{t,p}^{\text{Ave,EVs}}$	Average total charging vehicles in each EPL (kW).
P_t^{Wind}	Output power of wind system (kW).
$\bar{P}_p^{\text{CH/DCH,ES}}$	Maximum charging and discharging rate of EPL energy storage (kW).
$\bar{P}^{\text{E,EPL}}$	Maximum electricity trading between EPLs and MCES (kW).

$\bar{P}^{\text{MT,EPL}}$	Maximum electricity generation of EPL micro-turbine unit (kW).
$\underline{SoC}_p^{\text{EPL}}$	Minimum SOC of EPL energy storage (kWh).
$\overline{SoC}_p^{\text{EPL}}$	Maximum SOC of EPL energy storage (kWh).
$\delta^{\text{BO/CHP}}$	Efficiency of boiler/CHP.
$\delta^{\text{ES,EPL}}$	Cost coefficient of storage unit (\$/kWh).
η^{TS}	Heat storage efficiency.
$\zeta^{\text{SS,Des}}$	Desired self-sufficiency level (%).
$\pi_t^{\text{E,Buy/Sell}}$	Electricity buying/selling price (\$/kWh).
$\pi_t^{\text{H,Buy/Sell}}$	Heat buying/selling price (\$/kWh).
$\pi_t^{\text{G,Buy}}$	Gas buying price (\$/kWh).
$\pi_t^{\text{E,UP/DN}}$	Electricity upward/downward DRP price (\$/kWh).
$\pi_t^{\text{T,UP/DN}}$	Heat upward/downward DRP price (\$/kWh).
π^{SS}	Incentive/penalty price (\$/%).
$\pi_t^{\text{E,EPL}}$	Price of electricity trading between MCES and EPLs (\$/kWh).
π_t^{EV}	Price of soled energy to vehicles (\$/kWh).
$\vartheta^{\text{E}}, \vartheta^{\text{T}}$	Participation of electrical/heat demands in DRP.

D. Variables

MCES^{OBF}	Total operation cost of MCES (\$).
C_t^{E}	Cost of power exchange of MCES (\$).
$C_t^{\text{E,DR}}$	Cost of electrical DRP (\$).
C_t^{G}	Cost of gas exchange (\$).
C_t^{H}	Cost of heat exchange (\$).
$C_t^{\text{T,DR}}$	Cost of heat DRP (\$).
C_t^{SS}	Cost of self-sufficiency (\$).
E_t^{TS}	Heat storage SOC of heat storage (kWh).
$EL_t^{\text{DR}}, TL_t^{\text{DR}}$	Electricity/Heat demands after DRP (kW).
$G_t^{\text{G,Buy}}$	Buying gas from the upstream network (kW).
GB_t^{BO}	Gas consumption of boiler unit (kW).
GC_t^{CHP}	Gas consumption of CHP unit (kW).
$H_t^{\text{CH/DCH,TS}}$	Charging/Discharging heat of storage unit (kW).
$H_t^{\text{H,Buy/Sell}}$	Buying/selling heat from/to the grid (kW).
H_t^{BO}	Output heat of boiler unit (kW).
H_t^{CHP}	Output heat of CHP unit (kW).
I_t^{CHP}	Binary variable of CHP unit.
$I_t^{\text{CH/DCH,TS}}$	Charging/Discharging binary variables of the heat storage unit.
$I_t^{\text{E,Buy/Sell}}$	Buying/Selling binary variables of electricity from/to the grid.
$I_t^{\text{H,Buy/Sell}}$	Buying/Selling binary variables of heat from/to the grid.
$I_t^{\text{E,UP/DN}}$	Binary variables of upward/downward electrical DRP.
$I_t^{\text{T,UP/DN}}$	Binary variables of upward/downward heat DRP.
$J_{t,p}^i$	Slack variables of lower-level constraints.
P_t^{CHP}	Output power of CHP unit (kW).

$P_t^{\text{E,Buy/Sell}}$	Buying/Selling electricity from/to the grid (kW).
$P_{t,p}^{\text{E,EPL}}$	Electricity trading with the EPLs (kW).
$P_{t,p}^{\text{MT,EPL}}$	Output power of micro-turbine unit (kW).
$P_{t,p}^{\text{CH/DCH,ES}}$	Charging/Discharging of EPL energy storage (kW).
$SoC_{t,p}^{\text{EPL}}$	SOC of EPL energy storage (kWh).
ζ_t^{SS}	Self-sufficiency level (%).
$\mu_t^{\text{E,UP/DN}}$	Upward/Downward electricity DRP (kW).
$\mu_t^{\text{T,UP/DN}}$	Upward/Downward heat DRP (kW).
$\eta_{t,p}^i$	Dual variables.

I. INTRODUCTION

A. Motivation and Background

THE transitions to a low-carbon and sustainable energy system requires the mixing of various electricity assets, providers, and technologies. Electric vehicles (EVs) are one of the most promising technologies that can contribute to the decarbonization of the transportation sector and reduce emissions [1]. However, the large-scale penetration of EVs poses challenges to the planning and operation of the energy system, such as grid congestion and power quality issues [2]. The use of electric parking lots (EPLs) as intermediate entities between EVs and the grid can be considered a potential solution to address some of the challenges associated with the massive integration of EVs [3]. EPLs can optimize the charging and discharging schedules of EVs based on energy prices, network conditions, and the preferences of EV owners. As discussed in [3], EPLs are the active parts of the multi-carrier electricity system (MCES).

Despite the numerous benefits of incorporating EPLs into multi-energy systems, it can introduce complexities to the structure [4]. The MCES operator strives to minimize operational costs by engaging in the upstream energy networks and local energy trading with the EPLs. Conversely, the EPLs aim to maximize operational profits by participating in local energy trading with the MCES operator. This dynamic can be appropriately analyzed by the Stackelberg game theory, where bi-level optimization serves as a key mathematical tool for managing such strategic interactions. Furthermore, in addressing the upper level of this bi-level optimization problem, the MCES operator encounters uncertainties related to PV and wind generation, which can be effectively modeled using bi-level multi-objective information gap decision theory (MO-IGDT). IGDT is an effective approach for modeling optimization problems under severe uncertainty, such as the uncertainty of EPLs, without requiring probability distributions [5]. It also provides flexibility in risk attitudes, balancing robustness with opportunity in uncertain environments. MO-IGDT extends these capabilities to non-deterministic optimization problems with multiple sources of uncertainty. Hence, a powerful mathematical framework in the form of a bi-level multi-objective optimization model is developed to address the complex problem of MCES with EPLs.

B. Literature Review

In the last decade, the transition from conventional energy generation systems to decentralized, decarbonized, and democratized energy systems has gained significant attention worldwide. EVs are considered a key part of the energy transition. To enhance the scheduling of EVs within the energy system, their charging and discharging processes are integrated into the EPLs. Given the significance of scheduling EPLs within the energy system, numerous studies have addressed this crucial issue in the literature. For instance, a study in [6] investigates the stochastic bi-level coordination of an active distribution network and a renewable-based microgrid, considering the integration of EPLs into the electricity system without accounting for other energy carriers. The work in [7] proposes a robust two-stage optimization model for allocating intelligent Electric Power Loads (EPLs) in an electrical distribution network. Also, the role of EPLs in the energy communities is explored by [8]. The results demonstrate the benefits that EVs can offer to electrical energy communities when they are optimally utilized, underscoring their potential to improve both the efficiency and economy of the system.

Several recently published papers suggest that EPLs can be integrated into an MCES to enhance its economic performance. In [9], it is highlighted that the development of a risk-embedded scheduling strategy for EPLs and combined cooling, heating, and power systems within a residential energy system represents a crucial impact on the economic operation. In [10], a robust scenario-based concept is presented for the stochastic energy management of an energy system containing an intelligent parking lot. However, these studies do not treat EPLs as economic agents, thereby ignoring the interaction between MCES operators and EPL operators. This oversight may hinder the EPL's active and efficient participation in MCES.

On the other hand, MCESs serve as platforms for integrating distributed energy resources (DERs) and energy performance levels (EPLs). A key advantage stemming from the increased adoption of DERs is the augmentation of self-sufficiency [11]. The notion of self-sufficiency within local energy systems is intrinsically linked to reducing dependence on external energy grids [12]. Numerous studies in the literature have examined the role of self-sufficiency programs in the energy sector. For instance, the work in [13] proposes a self-sufficient model for implementing the concept of nearly zero-energy buildings. The work in [14] evaluates the enhancement of energy self-sufficiency in residential buildings through the utilization of solar-assisted heat pumps and various thermal and electrical storage solutions. The concept of self-sufficiency in renewable energy microgrids is explored in [15]. Additionally, [16] analyzes a PV unit and supercapacitor energy system to bolster self-consumption and self-sufficiency. However, these studies have yet to introduce formal and practical programs that account for the preferences of MCESs in their engagement with self-sufficiency initiatives.

The interaction between the MCES and EPLs can be modeled using various optimization approaches, depending on the structure of the decision-making process, market mechanisms,

and system constraints. Traditional centralized optimization models treat the MCES and EPLs as a single entity, solving a global optimization problem to minimize costs or maximize efficiency [17], [18]. However, such models often overlook the independent objectives and strategic behaviors of individual market participants. Additionally, these centralized optimization models may encounter computational burden issues.

The high penetration rate of DERs, such as PV systems and wind turbines, within an MCES poses another significant challenge regarding their uncertain generation, which warrants attention. Therefore, effective uncertainty management of DERs emerges as one of the essential issues to address from the MCES operator perspective. The bi-level IGDT approach is one of the well-known uncertainty models in the energy system. For instance, the work in [19] presents a bi-level IGDT profit maximization model based on game theory for microgrid aggregators that incorporates demand response programs (DRPs). In [20], the bi-level MO-IGDT is employed to address uncertainties in electricity prices, distributed energy resources (DERs), and loads for a virtual power plant. Moreover, some papers advocate adopting the bi-level MO-IGDT approach to model uncertainties, citing its enhanced accuracy and comprehensiveness. In this regard, the work in [21] optimizes the scheduling of low-carbon MCES integrated with hydrogen refueling stations and EPLs using a bi-level MO-IGDT approach. The operation problem of EPLs within the MCES is framed as a single-level problem, while the multi-objective aspect of the MO-IGDT is tackled through the epsilon-constrained approach. In [22], a stochastic MO-IGDT approach, which includes both endogenous and exogenous scenarios and is formulated as a nested bi-level optimization model, is presented for the operation optimization of DER aggregators.

In summary, the literature review reveals a research gap regarding the interaction between EPLs as economic agents and the MCES operator. Additionally, the participation of the MCES in self-sufficiency programs to facilitate the smooth operation of the upstream grid remains a challenge. Moreover, to the best of the author's knowledge, the uncertainty of MCES energy resources has not been addressed using a nested bi-level MO-IGDT approach.

C. Contributions

To address the above-mentioned gaps, this paper proposes a novel structure to integrate EPLs into an MCES using a bi-level Stackelberg game theory approach. The MCES operator acts as the leader and minimizes the MCES cost by participating in the upstream energy market at the upper level of the bi-level approach. The EPL operators act as the followers and maximize their profits by participating in the local energy market between the MCES operator and themselves at the lower level. At the same time, the MCES operator faces uncertainties from wind and PV generation in the MCES, which can affect the performance, feasibility, and robustness of the solutions, as well as the satisfaction of the self-sufficiency contracts. Therefore, we employ a bi-level MO-IGDT approach to address the uncertainties at the upper level of the Stackelberg game problem, resulting in a nested

bi-level optimization model. The MO-IGDT approach provides robust solutions against uncertainties without requiring detailed knowledge of their probability distributions. Unlike parametric approaches, such as stochastic programming, which rely on predefined probability distributions, MO-IGDT does not require such data. Additionally, unlike robust optimization approaches, it does not require predefined bounded intervals for uncertain variables. Instead, these intervals are optimized within the MO-IGDT methodology itself by maximizing robustness against uncertainties.

Moreover, the proposed Stackelberg game approach is an appropriate framework for this problem because it captures the hierarchical relationship between the MCES operator and the EPL operators. In traditional distributed algorithms, such as the alternating direction method of multipliers (ADMM), entities are typically treated equally, and the problem is split into sub-problems that are solved iteratively. However, these algorithms may not fully capture the economic and strategic behaviors and interactions that arise from the different objectives and decision-making processes of the MCES and EPL operators. This distinction is particularly important in our case, as it allows the framework to effectively incorporate elements, such as the MCES operator's participation in upstream energy markets and self-sufficiency programs, alongside the profit-maximization goals of the EPL operators. The Stackelberg game framework enables the MCES operator to anticipate and influence the responses of EPL, leading to an optimized equilibrium that balances system-wide efficiency and individual profitability.

In contrast, ADMM primarily focuses on computational efficiency through decentralized decision-making but may not explicitly model strategic interactions and economic incentives within hierarchical energy markets. The Stackelberg game framework ensures that the decision-making process reflects the operational roles of MCES and EPLs, allowing the MCES to design incentives that align with EPL objectives while considering uncertainties in renewable generations. Therefore, the Stackelberg game provides an effective modeling framework for this study. The main contributions of this paper are as follows:

- Contribution #1) Unlike the centralized approach in [17], [18], this paper proposes the integration of EPLs into an MCES through the Stackelberg game theory approach, which captures the complex interactions between different entities, resulting in a more advanced modeling framework.
- Contribution #2) In contrast to [23], which lacks an incentive/penalty mechanism for MCES participation in the upstream self-sufficiency programs, the proposed model includes this mechanism, ensuring alignment with self-sufficiency programs and motivating participation.
- Contribution #3) The operation of MCES + EPLs, considering uncertainties of PV and wind generations, is optimized by a nested bi-level MO-IGDT approach. The structure, function, and application of the proposed nested bi-level optimization approach are different from those of the nested bi-level optimization model of [22].

To further differentiate the roles of Contribution #1 and Contribution #3, it is important to highlight that they are conceptually distinct and serve different purposes, each with its own application. These contributions are independent, meaning that Contribution #1 can be applied without Contribution #3, and vice versa. Contribution #1 introduces a Stackelberg game formulation that enables hierarchical decision-making, making it applicable even in deterministic settings where uncertainty is not a major concern. In contrast, Contribution #3 focuses on uncertainty modeling through a multi-objective IGDT-based nested bi-level optimization, which can be used in uncertainty-aware optimization problems regardless of the decision-making structure. While they can be integrated to form a more comprehensive framework, each contribution retains its unique novelty, role, and applicability within the proposed MCES + EPLs operation optimization approach.

D. Main Assumptions

This paper assumes that the merged problem, obtained by transforming the bi-level Stackelberg game into a single-level optimization problem, is solved by the MCES operator acting as the leader. However, the interactions between the MCES and EPLs as well as the objectives and constraints of the followers are carefully modeled in the proposed approach. To achieve this, the leader must have access to the relevant information regarding the followers' lower-level objectives, constraints, and parameters. The study emphasizes methodological and theoretical contributions, leaving practical privacy concerns (e.g., safeguarding the data of followers) outside its scope. Additionally, the bi-level optimization problem is reformulated into a single-level Mixed Integer Linear Programming (MILP) using Karush-Kuhn-Tucker (KKT) conditions, under the assumptions of convexity and Slater's condition [24], to ensure convergence and computational feasibility.

II. THE PROPOSED FRAMEWORK

The proposed Stackelberg game unfolds as a strategic and iterative process between the MCES operator and EPL operators. Initially, the MCES operator strategically formulates decisions to minimize system costs, anticipating responses from the EPL operators. Subsequently, the EPL operators, acting as followers, influenced by the MCES operator's decisions, respond by maximizing their profits in the local energy market. This strategic interplay iteratively progresses as the leader and followers adjust their strategies, ultimately converging to a stable Stackelberg equilibrium point. At this equilibrium point, both the leader and followers achieve optimal outcomes, ensuring efficient operation of the energy market within the multi-carrier energy system. Fig. 1 illustrates the proposed nested bi-level MO-IGDT framework to address the mentioned Stackelberg game. In the proposed approach, a bi-level optimization problem is depicted, wherein the MCES operator minimizes the MCES operation cost at the outer upper level while determining the energy prices. At the outer lower level, the EPLs maximize their operational profits and determine the exchanged powers. Moreover, the proposed framework employs the MO-IGDT approach to address uncertainties

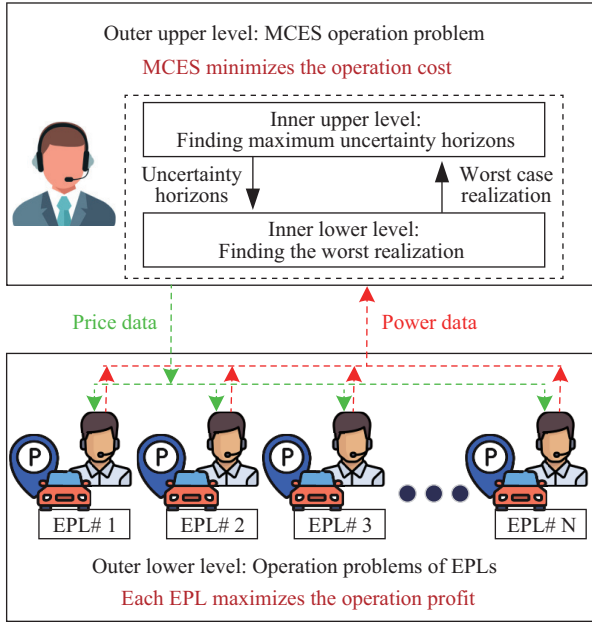


Fig. 1. Proposed nested bi-level MO-IGDT approach.

associated with the generation of PV and wind. To address this, another bi-level optimization model is formulated at the outer upper level of the main framework, as depicted in Fig. 1.

The primary objective of the inner upper level is to maximize the uncertainty horizons concerning PV and wind generations. The primary objective of the inner lower level is to determine the worst-case scenario for MCES operational costs.

The proposed nested bi-level MO-IGDT optimization problem, illustrated in Fig. 1, presents a complex hierarchical structure. To tackle this:

1) The nested bi-level MO-IGDT model is first transformed into a bi-level MO-IGDT problem by identifying the worst-case uncertainty realization as shown in Fig. 2.

2) Subsequently, KKT conditions are applied to reformulate the bilevel MO-IGDT problem as a single-level multi-objective optimization problem (Fig. 2), as detailed in the Appendix. This approach preserves the leader-follower interactions while enabling efficient computation. The strong duality principle ensures that this KKT-based reformulation yields solutions equivalent to those of the original lower-level problem, thereby ensuring convergence to the Stackelberg equilibrium [24].

3) Finally, a lexicographic approach transforms the problem into single-level, single-objective MILP problems (Fig. 2), which can be solved using commercial solvers such as CPLEX.

III. DETERMINISTIC BI-LEVEL OPTIMIZATION APPROACH

This section introduces a deterministic bi-level optimization approach aimed at modeling the Stackelberg game between the MCES operator and EPLs' operators. As this deterministic approach does not consider the uncertainties associated with PV and wind generation, it only involves outer bi-level optimization without inner optimization (Fig. 1).

The first and second parts of this section address the upper and lower levels of this deterministic bi-level problem,

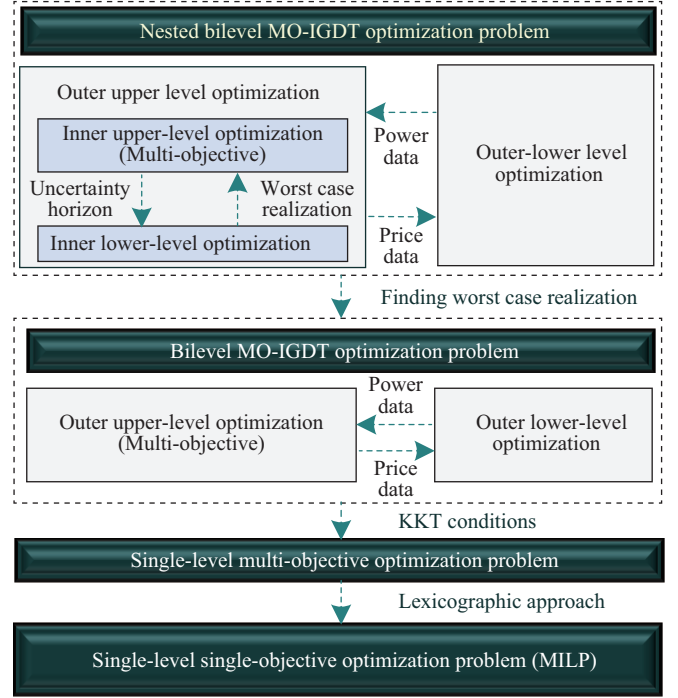


Fig. 2. The execution process of the proposed framework.

respectively. This bi-level optimization problem is converted to a single-level optimization problem using the KKT approach, as presented in the Appendix.

A. Upper Level: MCES Cost Minimization

The upper-level optimization problem is formulated as (1)–(41):

Min MCES^{OBF} :

$$\text{MCES}^{\text{OBF}} = \sum_{t=1}^{N_t} (C_t^E + C_t^H + C_t^G + C_t^{E,\text{DR}} + C_t^{T,\text{DR}} + C_t^{\text{SS}}) \quad (1)$$

s.t.

$$C_t^E = \pi_t^{E,\text{Buy}} P_t^{E,\text{Buy}} - \pi_t^{E,\text{Sell}} P_t^{E,\text{Sell}} + \sum_{p=1}^{N_p} \pi_t^{E,\text{EPL}} P_{t,p}^{E,\text{EPL}} \quad \forall t \quad (2)$$

$$C_t^H = \pi_t^{H,\text{Buy}} H_t^{H,\text{Buy}} - \pi_t^{H,\text{Sell}} H_t^{H,\text{Sell}} \quad \forall t \quad (3)$$

$$C_t^G = \pi_t^{G,\text{Buy}} G_t^{G,\text{Buy}} \quad \forall t \quad (4)$$

$$C_t^{E,\text{DR}} = \pi_t^{E,\text{UP}} \mu_t^{E,\text{UP}} + \pi_t^{E,\text{DN}} \mu_t^{E,\text{DN}} \quad \forall t \quad (5)$$

$$C_t^{T,\text{DR}} = \pi_t^{T,\text{UP}} \mu_t^{T,\text{UP}} + \pi_t^{T,\text{DN}} \mu_t^{T,\text{DN}} \quad \forall t \quad (6)$$

$$C_t^{\text{SS}} = \pi^{\text{SS}} (\zeta_t^{\text{SS,Des}} - \zeta_t^{\text{SS}}) \quad \forall t \quad (7)$$

$$\left(1 - \frac{P_t^{E,\text{Buy}}}{EL_t}\right) 100 \geq \zeta_t^{\text{SS}} \quad \forall t \quad (8)$$

$$P_t^{\text{CHP}} - P_A^{\text{CHP}} - \frac{P_A^{\text{CHP}} - P_B^{\text{CHP}}}{H_A^{\text{CHP}} - H_B^{\text{CHP}}} (H_t^{\text{CHP}} - H_A^{\text{CHP}}) \leq 0 \quad \forall t \quad (9)$$

$$P_t^{\text{CHP}} - P_B^{\text{CHP}} - \frac{P_B^{\text{CHP}} - P_C^{\text{CHP}}}{H_B^{\text{CHP}} - H_C^{\text{CHP}}} (H_t^{\text{CHP}} - H_B^{\text{CHP}}) \geq -(1 - I_t^{\text{CHP}})M \quad \forall t \quad (10)$$

$$P_t^{\text{CHP}} - P_C^{\text{CHP}} - \frac{P_C^{\text{CHP}} - P_D^{\text{CHP}}}{H_C^{\text{CHP}} - H_D^{\text{CHP}}} (H_t^{\text{CHP}} - H_C^{\text{CHP}}) \geq -(1 - I_t^{\text{CHP}})M \quad \forall t \quad (11)$$

$$0 \leq P_t^{\text{CHP}} \leq P_A^{\text{CHP}} \quad \forall t \quad (12)$$

$$0 \leq H_t^{\text{CHP}} \leq H_B^{\text{CHP}} \quad \forall t \quad (13)$$

$$P_t^{\text{CHP}} = GC_t^{\text{CHP}} \delta^{\text{CHP}} \quad \forall t \quad (14)$$

$$\underline{H}^{\text{BO}} \leq H_t^{\text{BO}} \leq \overline{H}^{\text{BO}} \quad \forall t \quad (15)$$

$$H_t^{\text{BO}} = GB_t^{\text{BO}} \delta^{\text{BO}} \quad \forall t \quad (16)$$

$$E_t^{\text{TS}} = E_{t-1}^{\text{TS}} + H_t^{\text{CH,TS}} \eta^{\text{TS}} - H_t^{\text{DCH,TS}} (1/\eta^{\text{TS}}) \quad \forall t \quad (17)$$

$$\underline{E}^{\text{TS}} \leq E_t^{\text{TS}} \leq \overline{E}^{\text{TS}} \quad \forall t \quad (18)$$

$$0 \leq H_t^{\text{CH,TS}} \leq I_t^{\text{CH,TS}} \overline{H}^{\text{CH,TS}} \quad \forall t \quad (19)$$

$$0 \leq H_t^{\text{DCH,TS}} \leq I_t^{\text{DCH,TS}} \overline{H}^{\text{DCH,TS}} \quad \forall t \quad (20)$$

$$I_t^{\text{CH,TS}} + I_t^{\text{DCH,TS}} \leq 1 \quad \forall t \quad (21)$$

$$0 \leq \mu_t^{\text{E,UP}} \leq \vartheta^{\text{E}} I_t^{\text{E,UP}} EL_t \quad \forall t \quad (22)$$

$$0 \leq \mu_t^{\text{E,DN}} \leq \vartheta^{\text{E}} I_t^{\text{E,DN}} EL_t \quad \forall t \quad (23)$$

$$\sum_{t=1}^{N_t} \mu_t^{\text{E,UP}} = \sum_{t=1}^{N_t} \mu_t^{\text{E,DN}} \quad \forall t \quad (24)$$

$$I_t^{\text{E,UP}} + I_t^{\text{E,DN}} \leq 1 \quad \forall t \quad (25)$$

$$EL_t^{\text{DR}} = EL_t + \mu_t^{\text{E,UP}} - \mu_t^{\text{E,DN}} \quad \forall t \quad (26)$$

$$0 \leq \mu_t^{\text{T,UP}} \leq \vartheta^{\text{T}} I_t^{\text{T,UP}} TL_t \quad \forall t \quad (27)$$

$$0 \leq \mu_t^{\text{T,DN}} \leq \vartheta^{\text{T}} I_t^{\text{T,DN}} TL_t \quad \forall t \quad (28)$$

$$\sum_{t=1}^{N_t} \mu_t^{\text{T,UP}} = \sum_{t=1}^{N_t} \mu_t^{\text{T,DN}} \quad (29)$$

$$I_t^{\text{T,UP}} + I_t^{\text{T,DN}} \leq 1 \quad \forall t \quad (30)$$

$$TL_t^{\text{DR}} = TL_t + \mu_t^{\text{T,UP}} - \mu_t^{\text{T,DN}} \quad \forall t \quad (31)$$

$$0 \leq P_t^{\text{E,Buy}} \leq \overline{P}^{\text{E,Buy}} I_t^{\text{E,Buy}} \quad \forall t \quad (32)$$

$$0 \leq P_t^{\text{E,Sell}} \leq \overline{P}^{\text{E,Sell}} I_t^{\text{E,Sell}} \quad \forall t \quad (33)$$

$$I_t^{\text{E,Buy}} + I_t^{\text{E,Sell}} \leq 1 \quad \forall t \quad (34)$$

$$0 \leq H_t^{\text{H,Buy}} \leq \overline{H}^{\text{H,Buy}} I_t^{\text{H,Buy}} \quad \forall t \quad (35)$$

$$0 \leq H_t^{\text{H,Sell}} \leq \overline{H}^{\text{H,Sell}} I_t^{\text{H,Sell}} \quad \forall t \quad (36)$$

$$I_t^{\text{H,Buy}} + I_t^{\text{H,Sell}} \leq 1 \quad \forall t \quad (37)$$

$$0 \leq G_t^{\text{G,Buy}} \leq \overline{G}^{\text{G,Buy}} \quad \forall t \quad (38)$$

$$H_t^{\text{H,Buy}} - H_t^{\text{H,Sell}} - H_t^{\text{CH,TS}} + H_t^{\text{DCH,TS}} + H_t^{\text{CHP}} + H_t^{\text{BO}} = TL_t^{\text{DR}} \quad \forall t \quad (39)$$

$$G_t^{\text{G,Buy}} - GB_t^{\text{BO}} - GC_t^{\text{CHP}} = GL_t \quad \forall t \quad (40)$$

$$P_t^{\text{E,Buy}} - P_t^{\text{E,Sell}} + P_t^{\text{CHP}} + P_t^{\text{PV}} + P_t^{\text{Wind}} + \sum_{p=1}^{N_p} P_{t,p}^{\text{E,EPL}} = EL_t^{\text{DR}} \quad \forall t \quad (41)$$

represents the electricity trading cost, encompassing expenses incurred for purchasing electricity from the upstream grid, revenue earned from selling electricity back to the grid, and charges for trading electricity with EPLs. Equation (3) describes the cost of heat transactions, including expenditures for buying heat from the upstream grid and income generated from selling heat to the grid. (4) accounts for the expense of natural gas purchased from the upstream grid, representing the operational costs tied to gas consumption within the MCES system. The electrical and thermal demand response costs are conducted using (5) and (6). Equation (7) represents the cost of self-sufficiency due to deviations from the desired self-sufficiency level. Constraint (8) defines the self-sufficiency constraint, ensuring that the self-sufficiency ratio remains above a certain threshold—constraints (9)–(11) model the feasible region of the CHP unit. Constraints (12) and (13) limit the power and heat output of the CHP unit and (14) expresses its gas input [4]. The operation constraints of the boiler unit are presented in (15) and (16). The operation constraints of the heat storage system are (17)–(21) [25]. Equation (17) shows the hourly stored thermal energy, which is bounded by (18). Constraints (19) and (20) represent the maximum and minimum values of charging and discharging thermal energy and (21) control the operation mode of the thermal energy storage unit. The electrical load-shifting DRP is modeled by (22)–(26). The limitations associated with increasing and decreasing demand are formulated in (22) and (23). Equation (24) guarantees the balance between the upward and downward electrical DRPs. The impossibility of simultaneously executing upward and downward DRPs is stated in (25), and finally, the amount of demand after DRP implementation is obtained as in (26). The thermal load-shifting DRPs can be formulated by (27)–(31) [4]. Constraint (27) specifies the upper and lower bounds for upward thermal demand response based on the system's capacity and activation status. Constraint (28) defines the bounds for downward thermal demand response, ensuring it stays within the system's operational limits. Equation (29) balances total thermal upward and downward adjustments over the entire operation time horizon, ensuring no long-term imbalance. Constraint (30) ensures that thermal upward and downward demand response cannot occur simultaneously at a given time. Equation (31) represents the adjusted total thermal load after accounting for thermal upward and downward demand response adjustments. The level of exchanged electricity, heat, and gas with the upstream network is limited by (32)–(38). In this context, electricity purchases and sales are constrained by (32) and (33), respectively. Constraint (34) prevents simultaneous buying and selling of electricity from/to the upstream grid. Similarly, (35) and (36) regulate the purchase and sale of heat from/to the grid, while (37) ensures that heat is not simultaneously bought and sold from/to the upstream grid. Additionally, the quantity of gas purchased from the grid is restricted by (38). From the energy procurement point of view, the equilibrium point for different heat, gas, and electricity energy carriers within the MCES is ensured by (39), (40), and (41), respectively.

Equation (1) is the objective function of the upper-level optimization problem for the MCES operator. Equation (2)

B. Lower Level: EPLs Profit Maximization

This subsection presents the lower-level problem, where the EPL operators aim to maximize the EPL profit while meeting the EVs' needs. The optimization problem is addressed in (42)–(54) as follows:

$$\max \sum_{t=1}^{N_t} \left(\pi_t^{\text{E,EPL}} P_{t,p}^{\text{E,EPL}} - a_{t,p}^{\text{MT,EPL}} P_{t,p}^{\text{MT,EPL}} - \delta^{\text{ES,EPL}} (P_{t,p}^{\text{CH,ES}} + P_{t,p}^{\text{DCH,ES}}) + \pi_t^{\text{EV}} P_{t,p}^{\text{Ave,EVs}} \right) \quad \forall p \quad (42)$$

s.t.

$$J_{t,p}^1 = \text{SOC}_p^{\text{EPL}} - \text{SOC}_{t,p}^{\text{EPL}} \leq 0 : \eta_{t,p}^1 \quad \forall t, p \quad (43)$$

$$J_{t,p}^2 = \text{SOC}_{t,p}^{\text{EPL}} - \overline{\text{SOC}}_p^{\text{EPL}} \leq 0 : \eta_{t,p}^2 \quad \forall t, p \quad (44)$$

$$J_{t,p}^3 = -P_{t,p}^{\text{CH,ES}} \leq 0 : \eta_{t,p}^3 \quad \forall t, p \quad (45)$$

$$J_{t,p}^4 = P_{t,p}^{\text{CH,ES}} - \overline{P}_p^{\text{CH,ES}} \leq 0 : \eta_{t,p}^4 \quad \forall t, p \quad (46)$$

$$J_{t,p}^5 = -P_{t,p}^{\text{DCH,ES}} \leq 0 : \eta_{t,p}^5 \quad \forall t, p \quad (47)$$

$$J_{t,p}^6 = P_{t,p}^{\text{DCH,ES}} - \overline{P}_p^{\text{DCH,ES}} \leq 0 : \eta_{t,p}^6 \quad \forall t, p \quad (48)$$

$$\text{SOC}_{t,p}^{\text{EPL}} = \text{SOC}_{t-1,p}^{\text{EPL}} + P_{t,p}^{\text{CH,ES}} \eta_{t,p}^{\text{EPL}} - P_{t,p}^{\text{DCH,ES}} / \eta_{t,p}^{\text{EPL}} : \eta_{t,p}^7 \quad \forall t, p \quad (49)$$

$$P_{t,p}^{\text{DCH,ES}} - P_{t,p}^{\text{CH,ES}} - P_{t,p}^{\text{E,EPL}} + P_{t,p}^{\text{MT,EPL}} = P_{t,p}^{\text{Ave,EVs}} : \eta_{t,p}^8 \quad \forall t, p \quad (50)$$

$$J_{t,p}^9 = -P_{t,p}^{\text{E,EPL}} \leq 0 : \eta_{t,p}^9 \quad \forall t, p \quad (51)$$

$$J_{t,p}^{10} = P_{t,p}^{\text{E,EPL}} - \overline{P}_p^{\text{E,EPL}} \leq 0 : \eta_{t,p}^{10} \quad \forall t, p \quad (52)$$

$$J_{t,p}^{11} = -P_{t,p}^{\text{MT,EPL}} \leq 0 : \eta_{t,p}^{11} \quad \forall t, p \quad (53)$$

$$J_{t,p}^{12} = P_{t,p}^{\text{MT,EPL}} - \overline{P}_p^{\text{MT,EPL}} \leq 0 : \eta_{t,p}^{12} \quad \forall t, p \quad (54)$$

In (42) the objective function for each EPL is given. The first, second, third, and fourth terms of (42) represent the revenue of selling electricity to the upstream network, the operation cost of the micro-turbine unit, the energy storage leveled cost, and the revenue of the EPL operator from selling power to the EVs, respectively. The number of EVs arriving in each EPL for charging is a random parameter and its value is randomly generated using the Poisson distribution function [26]–[29]. The central energy storage in each EPL is modeled by (43)–(49) [4]. Constraints (43) and (44) represent the minimum and maximum capacity limits, respectively, for the state of charge (SOC) of the energy storage system for each EPL, ensuring the SOC stays within its allowable operating range. Constraints (45) and (46) ensure that the charging power for each EPL remains within the minimum and maximum allowable capacities, respectively. Similarly, constraints (47) and (48) guarantee that the discharging power for each EPL stays within the minimum and maximum allowable capacities, respectively. Equation (49) represents the SOC dynamic balance equation for the energy storage system of each EPL. The proposed model inherently prevents simultaneous charging and discharging without requiring binary variables, as the monotonicity of the economic objective function, given in (42), ensures that minimizing the negative cost term naturally discourages the simultaneous operation.

Additionally, considering the efficiency of the storage system further prevents concurrent charging and discharging, as doing so would lead to unnecessary energy loss and increased costs. This is consistent with the findings in [30], which demonstrate that such constraints are inherently upheld as a result of economic disincentives. The electrical energy balance in EPL is addressed in (50). The selling of electricity to the MCES is limited by (51) and (52). The output power of the micro-turbine unit is limited by (53) and (54). It should be mentioned that, in constraints (43)–(48) and (51)–(54), $J_{t,p}^i$ represents slack variables, and $\eta_{t,p}^i$ is the corresponding dual variable. These variables work together to satisfy the complementary slackness conditions, which are provided in the Appendix Section.

IV. NESTED BI-LEVEL MO-IGDT MODEL AND ITS SOLUTION APPROACH

A. Nested Bi-level MO-IGDT Model

The MCES operator encounters uncertainties stemming from DERs, which can escalate overall costs and jeopardize the feasibility of the solution. This paper uses the MO-IGDT optimization framework to address uncertainties in wind and PV generation, with the primary objective of providing a robust solution against such uncertainties. To achieve this, the deterministic bi-level optimization problem introduced earlier is transformed into its MO-IGDT robust counterpart using an inner bi-level optimization model embedded in the upper level of the deterministic bi-level problem (as shown in Fig. 1). This study adopts a risk-averse strategy for managing uncertainties in PV and wind power generations, reflecting practical considerations of the MCES operator. Energy system operators are typically more focused on minimizing potential losses caused by unfavorable deviations in renewable generations [31]. The risk-averse approach aligns with the MCES operator's primary goals of minimizing costs and ensuring system reliability against the worst-case realizations of uncertainties. While IGDT also supports risk-seeking strategies, these are more applicable to scenarios where decision-makers aim to exploit favorable uncertainty realizations for potential gains. Given the critical importance of robust and reliable operations in the MCES, the risk-averse strategy is deemed more suitable for this study [32]. To model the uncertainties inherent in the problem, envelope-bound models for forecast-type uncertainties are constructed, as outlined in (55)–(58).

$$P_t^{\text{PV}} \in U^{\text{PV}}(a^{\text{PV}}, \hat{P}_t^{\text{PV}}) \quad (55)$$

$$U^{\text{PV}}(a^{\text{PV}}, \hat{P}_t^{\text{PV}}) = \left| \frac{P_t^{\text{PV}} - \hat{P}_t^{\text{PV}}}{\hat{P}_t^{\text{PV}}} \right| \leq a^{\text{PV}} \quad (56)$$

$$P_t^{\text{Wind}} \in U^{\text{Wind}}(a^{\text{Wind}}, \hat{P}_t^{\text{Wind}}) \quad (57)$$

$$U^{\text{Wind}}(a^{\text{Wind}}, \hat{P}_t^{\text{Wind}}) = \left| \frac{P_t^{\text{Wind}} - \hat{P}_t^{\text{Wind}}}{\hat{P}_t^{\text{Wind}}} \right| \leq a^{\text{Wind}} \quad (58)$$

where $\hat{P}_t^{\text{PV}}$ and $\hat{P}_t^{\text{Wind}}$ are the forecasted PV and wind power values. Moreover, P_t^{PV} and P_t^{Wind} are the actual PV and wind power values. The inner bi-level optimization problem is constructed as follows:

1) Inner Upper Level:

The upper level of the inner bi-level MO-IGDT model is formulated as below:

$$\max(a^{PV}, a^{Wind}) \quad (59)$$

s.t.

$$MCES_{WC}^{OBF} \leq (1 + \beta)R_0 \quad (60)$$

Constraints (3)–(41) & (43)–(58)

$$\text{Constraints (A2)–(A7), (A9), (A10) \& (A12)} \quad (61)$$

The main objective of the inner upper-level optimization is to maximize the uncertainty horizons (a^{PV}, a^{Wind}) to find the most robust solution. The same uncertainty horizon is used for PV systems (a^{PV}) and the same uncertainty horizon is used for the wind generators (a^{Wind}) considering the typical geographical size of an MCES system within which the wind and solar regimes do not change significantly [33]. $MCES_{WC}^{OBF}$ in (60) shows the worst-case scenario (the worst MCES objective function value) that is determined by the inner lower level. Also, R_0 is the cost of the deterministic bi-level optimization problem ($MCES_{WC}^{OBF}$ in (1)). β is the cost deviation factor.

2) Inner Lower Level

The lower level of the inner bi-level MO-IGDT model, as presented in (62)–(65), aims to identify the worst realization characterized by the highest unfavorable deviations in uncertain variables.

$$MCES_{WC}^{OBF} = \max MCES^{OBF} \quad (62)$$

s.t.

$$(1 - a^{Wind,O})\hat{P}_t^{Wind} \leq P_t^{Wind} \leq (1 + a^{Wind,O})\hat{P}_t^{Wind} \quad (63)$$

$$(1 - a^{PV,O})\hat{P}_t^{PV} \leq P_t^{PV} \leq (1 + a^{PV,O})\hat{P}_t^{PV} \quad (64)$$

$$\text{Constraints (1) \& (61)} \quad (65)$$

The $a^{Wind,O}$ and $a^{PV,O}$ are the a^{Wind} and a^{PV} determined by the inner upper level.

The maximum net cost, as per (62)–(65), is evidently attained at the lowest DER generation. Accordingly, the inner bi-level optimization problem (59)–(65) can be converted to the single-level multi-objective optimization problem as (66)–(69) as follows:

$$\max(a^{PV}, a^{Wind}) \quad (66)$$

s.t.

$$MCES_{WC}^{OBF} = \left\{ \sum_{t=1}^{N_t} (C_t^E + C_t^H + C_t^G + C_t^{E,DR} + C_t^{T,DR} + C_t^{SS}) \right\} \leq (1 + \beta)R_0 \quad (67)$$

$$P_t^{E,Buy} - P_t^{E,Sell} + P_t^{CHP} + (1 - a^{PV})\hat{P}_t^{PV} + (1 - a^{Wind})\hat{P}_t^{Wind} + \sum_{p=1}^{N_p} P_{t,p}^{E,EPL} = EL_t^{DR} \quad (68)$$

$$\text{Constraint (61)} \quad (69)$$

where (67) and (68) stipulate the maximum MCES operational cost ($MCES_{WC}^{OBF}$) and electric energy equilibrium under the worst-case scenario of PV and wind variability.

B. The Multi-Objective Optimization Solution Approach

In the literature, various methods have been proposed to address multi-objective optimization problems, with the Lexicographic approach being a widely recognized method. This approach provides clear objective prioritization by sequentially optimizing objectives, making it more straightforward to implement compared to methods such as the normalized normal constraint, which involves balancing objectives with weights and identifying Pareto-optimal solutions. By focusing on one objective at a time, the Lexicographic approach reduces computational complexity and simplifies decision-making. The algorithm first optimizes the highest-priority objective, disregarding other objectives until an optimal solution for the primary objective is achieved. Subsequently, it moves to the next objective in the hierarchy, optimizing it within the feasible region defined by the solution of the previous objective. This iterative process continues until all objectives are addressed, resulting in a solution that reflects the predefined priority order and trade-offs between the objectives. In this study, the Lexicographic approach is applied within the MO-IGDT framework to address two competing objectives: maximizing robustness against PV and wind generation uncertainties. The prioritization of these objectives is determined by the MCES operator's preferences and experiences, with a focus on the most critical uncertainty. For instance, if the operator identifies PV generation uncertainty as having a greater impact on the system performance than wind generation uncertainty (e.g., when the PV generation capacity is much more than wind generation capacity and thus its uncertain fluctuations have a greater impact on the system performance), it is given a higher priority. The secondary uncertainty is then addressed within the feasible region defined by the primary objective. This approach mirrors practical decision-making, where system operators assess system vulnerabilities and prioritize objectives based on their impacts [21]. Based on the Lexicographic approach, if being immune to the PV uncertainty is a higher priority objective for the decision maker, the following optimization problem is solved and the optimal value of the a^{PV} is determined as:

$$\max a^{PV} \quad (70)$$

s.t.

$$\text{Constraints (67)–(69)} \quad (71)$$

After determining the optimal value of a^{PV} , which is denoted as $a^{PV,Opt}$, the second optimization problem is solved by considering $a^{PV,Opt}$ as follows:

$$\max a^{Wind} \quad (72)$$

s.t.

$$a^{PV} \geq a^{PV,Opt} \quad (73)$$

$$\text{Constraints (67)–(69)} \quad (74)$$

The proposed multi-objective optimization solution approach can be summarized as follows. Without loss of generality, we assume the PV uncertainty horizon has a higher priority.

Step 1: The deterministic optimization problem is solved and R_0 is determined.

Step 2: The cost deviation factor is initialized ($\beta = 0$).

Step 3: The optimization problem for the higher priority objective function, i.e., (70) and (71), is solved and $a^{PV,Opt}$ is determined.

Step 4: By substituting $a^{PV,Opt}$ in the second priority optimization problem (72)–(74), it is solved.

Step 5: β is increased by 0.1. If $\beta \leq 1$, go back to *Step 3*. Otherwise, stop the algorithm.

V. NUMERICAL STUDY

A. Input Data

An MCES, consisting of four EPLs, is employed to test the proposed model. The electrical and thermal energy prices are sourced from [25]. The energy demands of the MCES are shown in Fig. 3 [34]. The forecasted powers of PV and wind generation systems are obtained from [35]. The number of EVs arriving in each EPL for charging, illustrated in Fig. 4, is randomly generated according to the Poisson distribution function [26]–[29]. The gas price is assumed to be 0.07 \$/kWh. The upward and downward demand response price for both electrical and thermal energies is 0.05 \$/kWh. The maximum participation rate in DRPs for electrical and thermal energies is 20% [4]. The desired self-sufficiency level is 70%. The efficiency of the CHP unit and boiler unit is 60% and 85%, respectively [4]. The maximum output of the boiler unit is 200 kW. The minimum and maximum capacity of the thermal energy storage is 30 kWh and 300 kWh, respectively. Additionally, the thermal energy storage efficiency is 95% [4]. The maximum electricity, heat, and gas input to the MCES are 2500 kW, 2200 kW and 1000 kW. The capacity of the EPLs' energy storage is 150 kW and each EPL has a clean hydrogen micro-turbine with 200 kW capacity. The proposed model is solved using the CPLEX solver in the GAMS environment on a computer with an Intel Core i7 processor and 16 GB of RAM.

B. Results

In this subsection, the numerical results of the proposed model are provided. The first subsection presents the results of the deterministic bi-level model, while the second subsection covers the results of the proposed nested bi-level MO-IGDT model.

1) Results of the Deterministic Bi-level Model

The self-sufficiency program of the MCES can yield beneficial consequences for the energy system. To evaluate it, we assume that the upstream power system operator applies an incentive/penalty scheme to incentivize MCES participation in the self-sufficiency program under the self-sufficiency program proposed in this paper.

Table I illustrates the impact of the incentive/penalty and the percentage of self-sufficiency on the operation cost of the MCES. As depicted in Table I, it's evident that with the same incentive amount, the operation cost of MCES rises as the percentage of self-sufficiency increases (except for the zero incentive/penalty price). This trend highlights that an increase

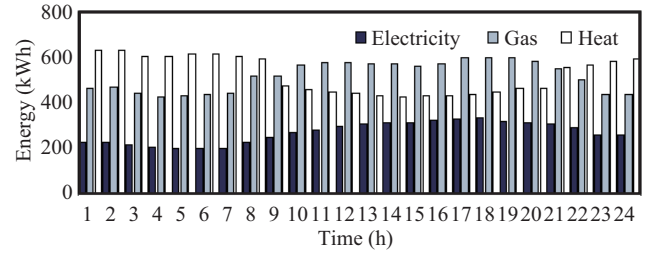


Fig. 3. The energy demands of the MCES.

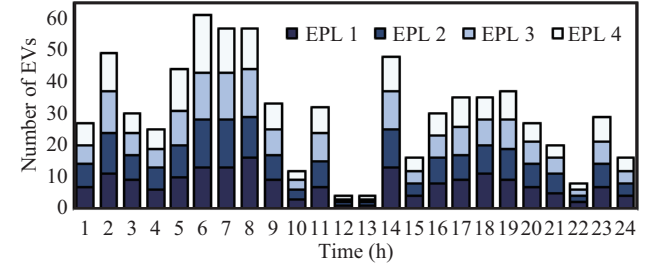


Fig. 4. Number of EVs arriving in each EPL.

TABLE I
SELF-SUFFICIENCY ANALYSIS RESULTS

Incentive/ Penalty price (\$/%)	Desired self-sufficiency level (%)				
	50	60	70	80	90
0	1963.9	1963.9	1963.9	1963.9	1963.9
0.05	1937.2	1949.1	1961.2	1973.3	1985.2
0.10	1883.9	1907.8	1931.7	1955.9	1979.6
0.15	1823.8	1859.9	1895.8	1931.2	1967.5
0.20	1763.7	1811.9	1859.8	1907.9	1955.7

in the desired self-sufficiency level, without a corresponding increase in the incentive payment from the upstream network, is unfavorable for the MCES. In such a scenario, the MCES would be compelled to utilize its high-cost energy resources to meet the desired self-sufficiency level of the upstream network, thereby imposing an additional financial burden on the MCES without commensurate compensation. Moreover, the table indicates that higher incentives significantly reduce costs when the desired level of self-sufficiency is low. For instance, at a desired self-sufficiency of 50%, increasing the incentive/penalty price from 0 to 0.20 lowers the cost from 1963.9 to 1763.7, as higher incentives further motivate the MCES to participate in self-sufficiency programs. At higher self-sufficiency levels (e.g., 90%), lower incentives (e.g., 0.05) result in higher costs due to the need to avoid penalties by using high-cost energy resources. This imposes an additional financial burden without adequate compensation. However, when incentives increase (e.g., 0.1–0.2), the operation cost decreases as the rewards from higher incentives outweigh the cost of using high-cost energy resources. The EPLs can participate in a local energy market with the MCES operator and sell their extra energy to the MCES to increase their operational profit. Fig. 5 shows the selling energy of each EPL to the MCES. The findings suggest that selling power to the MCES is more pronounced when the electrical price in the upstream network is high and the electrical demand is also high. EPLs feature a micro-turbine and a central energy storage

system, which significantly enhances the flexibility of their operations. The performance of the micro-turbine is illustrated in Fig. 6. As observed, the performance of the micro-turbine correlates closely with the selling energy to the MCES and the EVs arriving in the EPLs.

The energy exchange between the MCES and the upstream network is shown in Fig. 7. As depicted in Fig. 7, the MCES procures electricity from the upstream network during periods when the PV system is not generating any power and the electricity price is low. Additionally, the MCES sells the electric power to the upstream network during sunny hours. Furthermore, the purchase of gas is primarily linked to gas-fueled resources within the MCES, such as boilers and CHP units. The performance of the thermal energy storage system is shown in Fig. 8. The results indicate that the thermal storage charges during periods of low thermal load, i.e., hours 1–3, and discharges during peak hours, such as hour 5. Fig. 9 illustrates the performance of the electrical and thermal DRPs. The electrical demand rises during hours 1–2 when the energy price is low, while it decreases during peak hours 9–12 when the energy price is higher. Moreover, the load-shifting DRP moderates the peak thermal demand during hour 5 (Fig. 3), while increasing the thermal load during valley price hours 7 and 9.

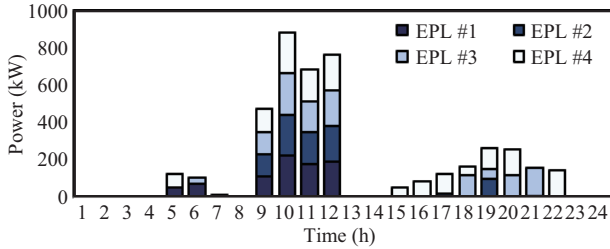


Fig. 5. Energy trading between EPLs and MCES.

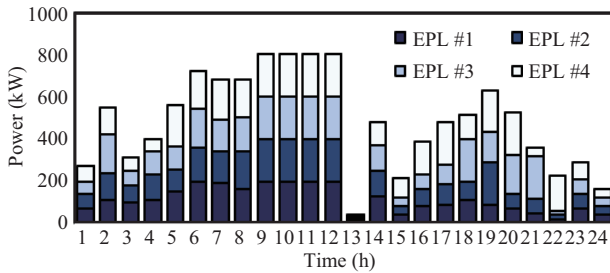


Fig. 6. Performance of micro-turbines of EPLs.

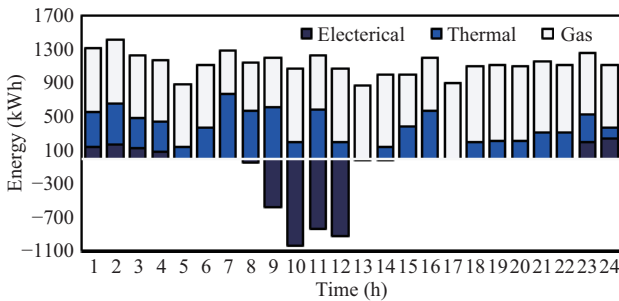


Fig. 7. Energy trading with the upstream grid.

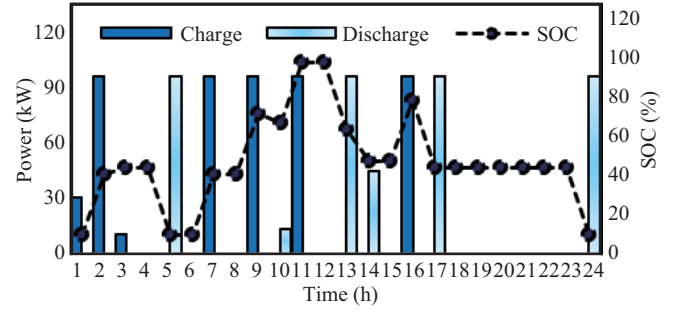


Fig. 8. Thermal energy storage performance.

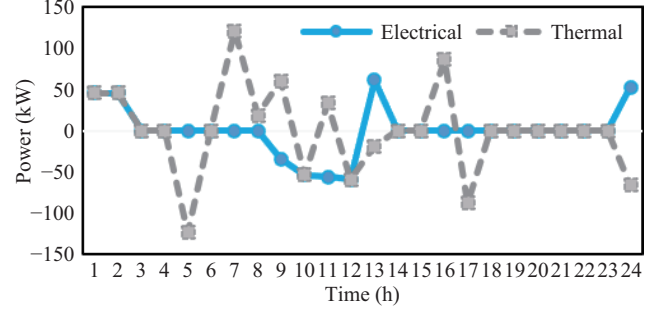


Fig. 9. Performance of electrical and thermal DRPs.

2) Results of Nested Bi-level MO-IGDT Model

In this subsection, the results obtained from the proposed nested bi-level MO-IGDT model are presented. Fig. 10 shows the impact of the cost deviation factor on the robustness against PV and wind uncertainties. The results show that the PV and wind robustness levels increase as the cost deviation factor increases. Furthermore, the results suggest that altering the cost deviation factor has a greater impact on the robustness of the PV system compared to the wind energy system. This outcome can be attributed to the limited working hours of the PV system and the higher priority of PV robustness over wind robustness in the lexicographic approach (see (70)–(74)). Therefore, PV robustness can be significantly increased with a small cost division. Fig. 11 illustrates the impact of the MO-IGDT risk-averse strategy on the exchanged power with the power grid. According to the figure, it is evident that as the cost deviation factor increases, the amount of purchased power increases while the amount of sold power decreases.

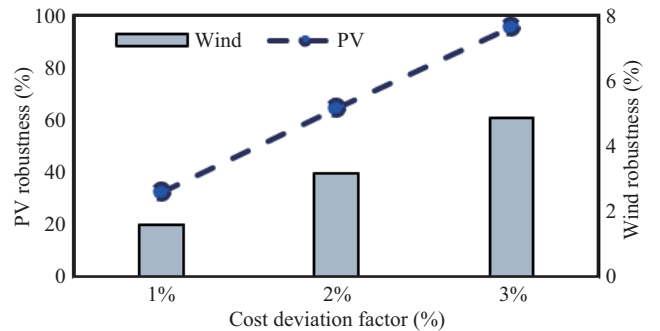


Fig. 10. PV and Wind robustness analyses.

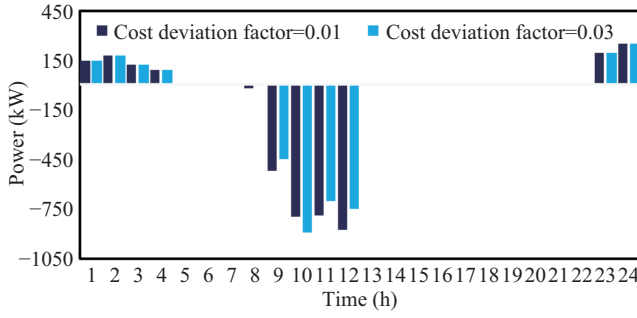


Fig. 11. Exchanged power with the power grid under different robustness levels (Positive: Purchasing power; Negative: Selling power).

This situation arises from the greater uncertainty in the horizons considered for the PV and wind outputs, compelling the operator to adopt a more robust approach, which results in higher power purchases and reduced power sales. The computational times for the deterministic bi-level model and the nested bi-level MO-IGDT model are 0.2 seconds and 0.5 seconds, respectively, showcasing the computational efficiency of the proposed approaches. The scalability of the proposed model, when applied to larger systems with an increased number of EPLs, can be assessed by evaluating the solving time performance of the deterministic bi-level model, as shown in Fig. 12. As seen, the solving time scales approximately linearly with the number of EPLs. For instance, when the number of EPLs increases from 4 to 64, the solving time grows from 0.2 s to 2.31 s, demonstrating the scalability of the proposed algorithm for larger systems with more EPLs.

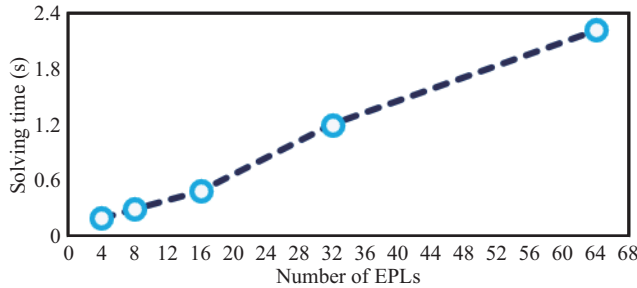


Fig. 12. The impact of the number of EPLs on the solving time performance.

C. Discussion

The numerical results validate the effectiveness of the proposed nested bi-level MO-IGDT approach in integrating EPLs into MCES operations while addressing uncertainties in renewable energy generation. The findings demonstrate that the Stackelberg game framework enables the MCES operator to strategically influence EPL decision-making strategically, leading to cost-efficient and balanced energy allocation strategies. The incorporation of MO-IGDT enhances uncertainty-aware decision-making, allowing the proposed approach to balance robustness against cost-effectiveness under uncertainties in PV and wind generation. The participation of MCES in self-sufficiency programs has a significant impact on operational cost reductions, depending on the incentive and penalty mechanisms applied by the upstream energy network. The

observed benefits of the self-sufficiency program reinforce the practical applicability of the proposed model in market-driven MCES operations. The results show that increasing incentive and penalty prices from 0 to 0.2 \$/% with a 50% self-sufficiency target can reduce MCES operation costs by 10.19%, demonstrating that economic incentives play a crucial role in MCES-EPL interactions.

A direct numerical comparison between the proposed approach and other methods is not feasible due to their fundamentally different structure and components. However, a qualitative comparison highlights their distinct characteristics. While the contributions outlined in the Introduction contrast significantly with those of prior studies, such as [17], [18], [22], [23], and [36], these distinctions are further highlighted and discussed here.

Unlike [17], which employs a multi-objective single-level optimization approach that independently optimizes multiple conflicting objectives—such as cost minimization and emission reduction—without explicitly capturing the interdependencies between decision-making entities, the proposed Stackelberg-game-based approach integrates a hierarchical leader-follower framework to model the strategic interactions between different energy market participants. The model in [18] focuses on optimizing the coordination of multi-carrier energy systems using a stochastic programming approach but does not incorporate market-driven participation incentives or hierarchical decision-making. However, the proposed study extends beyond uncertainty modeling by embedding a game-theoretic Stackelberg structure, enabling strategic pricing decisions that influence EPL participation. Methods, such as the ADMM optimization approach, used in energy system management, enable multiple entities to coordinate decision-making iteratively. For instance, [36] presented a distributed collaboration framework, based on ADMM, for peer-to-peer transactions in reconfigurable distribution networks, where prosumers optimize their local energy exchanges.

In contrast, the distribution system operator manages network constraints. While such decentralized approaches improve computational efficiency, they do not explicitly model leader-follower dynamics or the economic incentives that drive interactions between the MCES and EPL operators. In contrast, this paper introduces a bi-level Stackelberg game-based optimization framework, where the MCES operator serves as the leader and the EPL operators serve as followers. Unlike ADMM-based approaches, which treat all participating agents equivalently, our model explicitly captures the leader-follower dynamics, allowing the MCES operator to strategically influence the EPL operators' decisions rather than merely solving decentralized subproblems. This hierarchical structure is crucial in energy markets, where economic incentives and strategic decision-making have a significant impact on system operations.

Additionally, another key distinction lies in our nested bi-level MO-IGDT approach, which is different from a conventional bi-level structure constructed by integrating IGDT uncertainty management into the bi-level structure of the Stackelberg game. While [36] focuses on deterministic optimization, our method is fundamentally different, as it di-

rectly addresses uncertainties in renewable energy generation (wind and PV) without relying on predefined probability distributions. The proposed MO-IGDT framework enables robust decision-making, optimizing system operations under worst-case scenarios, which enhances robustness against uncertainties (i.e., fluctuating energy sources). This significant capability makes this paper more robust for real-world MCES applications where uncertainty plays a critical role in operational planning. The work in [22] explores the operation of DER aggregators using a nested bi-level stochastic MO-IGDT framework; however, it does not provide a detailed market-oriented structure for integrating EPLs as economic agents. Unlike [23], which only considers self-sufficiency as an index without incorporating an incentive and penalty mechanism to encourage or regulate self-sufficiency programs in the upstream energy market, the proposed model explicitly integrates such a mechanism. This ensures a more strategic and structured participation framework for an MCES operating under economic interactions with EPLs.

Similarly, regarding uncertainty modeling, a qualitative analysis provides valuable insights into how the proposed and existing approaches differ in their treatment of uncertainty, decision-making structures, and practical applicability.

Deterministic optimization assumes that all parameters are known with certainty and fails to account for real-world uncertainties. Consequently, it may lead to non-optimal or even infeasible solutions in practice when realized uncertainties, such as renewable generation variability, deviate from their expected values. In contrast, the nested bi-level MO-IGDT explicitly models uncertainties and provides a structured way to assess risk levels, making it more robust against uncertainties and more practical for managing PV and wind variability.

Stochastic programming optimizes expected outcomes based on scenarios and predefined probability distributions, requiring extensive scenario generation, which makes it computationally expensive for large-scale systems, such as MCES + EPLs. Additionally, stochastic programming does not provide robustness against uncertainties, as it focuses on optimizing an expected value rather than ensuring feasibility under worst-case scenarios. Unlike stochastic programming, the nested bi-level MO-IGDT does not require probability distributions and explicitly models uncertainties through envelope-bound models, offering greater flexibility for uncertainty characterization and modeling. Furthermore, the proposed approach not only provides robustness against uncertainties but also maximizes the uncertainty horizons, making it a more reliable approach for decision-making under uncertainty.

Robust optimization, which also avoids probabilistic modeling, differs from the proposed nested bi-level MO-IGDT in its treatment of uncertainty. Robust optimization focuses on worst-case scenarios within predefined uncertainty sets, ensuring feasibility under extreme conditions; however, it may lead to overly conservative solutions that can reduce operational efficiency. Additionally, robust optimization requires predefined uncertainty bounds, limiting adaptability to real-world renewable energy fluctuations. The nested bi-level MO-IGDT, on the other hand, offers an adjustable level of robustness, allowing decision-makers to dynamically balance

robustness and cost-effectiveness, making it particularly well-suited for integrating PV and wind into MCES. Furthermore, the proposed approach can be implemented more easily in practice because setting a threshold for the cost through the cost deviation factor is much simpler than defining bounded intervals for uncertain variables in robust optimization for MCES operators.

This qualitative comparison highlights the significant advantages of the proposed nested bi-level MO-IGDT approach in providing robust solutions against uncertainties, striking a balance between robustness and cost-effectiveness, and facilitating practical implementation in MCES + EPLs operation problems. The rationale behind developing and proposing this approach lies in its ability to bridge the gap between computational efficiency, strategic decision-making, and modeling real-world uncertainty.

The findings highlight several real-world applications of the proposed framework, particularly for MCES operators, policymakers, and energy market stakeholders. By incorporating a bi-level game-theoretic approach, the MCES operator can incentivize EPLs to participate in local energy markets, ensuring cost-effective and self-sufficient energy exchanges. The MO-IGDT-based nested bi-level optimization enables MCES operators to adjust risk preferences while maintaining economic sustainability proactively. The proposed framework offers a structured approach for integrating self-sufficiency programs, illustrating how incentive mechanisms can result in substantial operational cost reductions. The results suggest that a well-designed combination of Stackelberg game incentives and robust uncertainty modeling can improve market efficiency, making MCES operations more robust and economically viable.

VI. CONCLUSION

This paper applies Stackelberg game theory and MO-IGDT to integrate EPLs into MCES using a nested bi-level optimization model. The bi-level problems are simplified into single-level ones using KKT conditions and worst-case scenarios, then solved using Lexicographic optimization. Through the proposed model, EPLs can effectively exchange energy with the MCES, thereby increasing the profit of EPLs and decreasing the operation cost of MCES. Additionally, the participation of MCES in the self-sufficiency programs is modeled within a nested bi-level optimization framework. The proposed bi-level deterministic model and nested bi-level MO-IGDT model have been tested on an MCES with electricity, heat, and gas networks as well as four EPLs. The results indicate that 1) for a desired self-sufficiency level of 50%, increasing the incentive/penalty price of the self-sufficiency programs from 0 \$/% to 0.2 \$/% results in a decrease in the MCES operation cost by 10.19%, 2) the integration of EPLs reduces the MCES daily operational cost, 3) changing the cost deviation factor has a more significant impact on the robustness of the PV system compared to the wind energy system. This difference can be attributed to the limited operating hours of the PV system and the higher priority of the PV system robustness in the lexicographic approach, and 4) it can be concluded

that increasing the robustness level against the PV and wind generation uncertainties leads to an increase in the purchased power and a decrease in the sold power of the MCES from/to the upstream network.

APPENDIX

The bi-level optimization problem models the Stackelberg game between the MCES and EPL operators. It is converted into a single-level MILP problem using KKT conditions, which replace the convex follower problem. The Lagrangian function for each EPL optimization problem (42)–(54) is as follows:

$$L_p = \sum_{t=1}^{N_t} \left(\pi_t^{E,EPL} P_{t,p}^{E,EPL} - a_{t,p}^{MT,EPL} P_{t,p}^{MT,EPL} - \delta_{ES,EPL} (P_{t,p}^{CH,ES} + P_{t,p}^{DCH,ES}) + \pi_t^{EV} P_{t,p}^{Ave,EVs} \right) + \sum_{t=1}^{N_t} \left(\begin{aligned} & -\eta_{t,p}^1 (SoC_p^{EPL} - SoC_{t,p}^{EPL}) - \eta_{t,p}^2 (SoC_{t,p}^{EPL} - \bar{SoC}_p^{EPL}) \\ & -\eta_{t,p}^3 (-P_{t,p}^{CH,ES}) - \eta_{t,p}^4 (P_{t,p}^{CH,ES} - \bar{P}_p^{CH,ES}) - \\ & \eta_{t,p}^5 (-P_{t,p}^{DCH,ES}) - \eta_{t,p}^6 (P_{t,p}^{DCH,ES} - \bar{P}_p^{DCH,ES}) - \\ & \eta_{t,p}^7 (SoC_{t,p}^{EPL} - SoC_{t,p}^{EPL} - P_{t,p}^{CH,ES} \eta_{t,p}^{EPL} +) - \\ & \eta_{t,p}^8 (P_{t,p}^{DCH,ES} - P_{t,p}^{CH,ES} - P_{t,p}^{E,EPL} + P_{t,p}^{MT,EPL} - P_{t,p}^{Ave,EVs}) - \\ & \eta_{t,p}^9 (-P_{t,p}^{E,EPL}) - \eta_{t,p}^{10} (P_{t,p}^{E,EPL} - \bar{P}_{t,p}^{E,EPL}) - \\ & \eta_{t,p}^{11} (-P_{t,p}^{MT,EPL}) - \eta_{t,p}^{12} (P_{t,p}^{MT,EPL} - \bar{P}_{t,p}^{MT,EPL}) \end{aligned} \right) \quad (A1)$$

It should be noted that for each EPL in the lower level or follower problem, $\pi_t^{E,EPL}$ is considered as a parameter as it is determined by the MCES operator. Based on the Lagrange function, the KKT conditions are as follows:

$$\frac{\partial L_p}{\partial SoC_{t,p}^{EPL}} = \eta_{t,p}^1 - \eta_{t,p}^2 - \eta_{t,p}^7 + \eta_{t,p}^7 = 0 \quad \forall t, p \quad (A2)$$

$$\frac{\partial L_p}{\partial P_{t,p}^{CH,ES}} = -\delta_{ES,EPL} + \eta_{t,p}^3 - \eta_{t,p}^4 + \eta_{t,p}^{EPL} \eta_{t,p}^7 + \eta_{t,p}^8 = 0 \quad \forall t, p \quad (A3)$$

$$\frac{\partial L_p}{\partial P_{t,p}^{DCH,ES}} = -\delta_{ES,EPL} + \eta_{t,p}^5 - \eta_{t,p}^6 - \eta_{t,p}^7 / \eta_{t,p}^{EPL} - \eta_{t,p}^8 = 0 \quad \forall t, p \quad (A4)$$

$$\frac{\partial L_p}{\partial P_{t,p}^{E,EPL}} = \pi_t^{E,EPL} + \eta_{t,p}^8 + \eta_{t,p}^9 - \eta_{t,p}^{10} = 0 \quad \forall t, p \quad (A5)$$

$$\frac{\partial L_p}{\partial P_{t,p}^{MT,EPL}} = -a_{t,p}^{MT,EPL} - \eta_{t,p}^8 + \eta_{t,p}^{11} - \eta_{t,p}^{12} = 0 \quad \forall t, p \quad (A6)$$

$$\eta_{t,p}^1, \eta_{t,p}^2, \eta_{t,p}^3, \eta_{t,p}^4, \eta_{t,p}^5, \eta_{t,p}^6, \eta_{t,p}^7, \eta_{t,p}^8, \eta_{t,p}^9, \eta_{t,p}^{10}, \eta_{t,p}^{11}, \eta_{t,p}^{12} \geq 0 \quad (A7)$$

The complimentary slackness conditions are as follows:

$$J_{t,p}^i \eta_{t,p}^i = 0 \quad \forall i \in \{1-6, 9-12\} \quad (A8)$$

The above-mentioned constraints are non-linear. Considering the slackness conditions, the big-M method is used for the linearization as follows:

$$M(U_{t,p}^i - 1) \leq J_{t,p}^i \leq 0 \quad \forall i \in \{1-6, 9-12\} \quad (A9)$$

$$0 \leq \eta_{t,p}^i \leq MU_{t,p}^i \quad \forall i \in \{1-6, 9-12\} \quad (A10)$$

where $U_{t,p}^i$ is the binary variable and M is a sufficiently large positive constant. The nonlinear expression $\pi_t^{E,EPL} P_{t,p}^{E,EPL}$ in

(2), in the upper-level or leader problem, is replaced with linear expressions ($\pi_t^{E,EPL}$ is variable in the upper-level problem).

At first, according to the strong duality theory, the objective function of the dual problem (42)–(54) should be equal to the primal problem as follows:

$$\sum_{t=1}^{N_t} \left(\begin{aligned} & -\eta_{t,p}^1 SoC_p^{EPL} + \eta_{t,p}^2 \bar{SoC}_p^{EPL} + \eta_{t,p}^4 \bar{P}_p^{CH,ES} \\ & + \eta_{t,p}^6 \bar{P}_p^{DCH,ES} + \eta_{t,p}^8 P_{t,p}^{Ave,EVs} + \eta_{t,p}^{10} \bar{P}_{t,p}^{E,EPL} \\ & + \eta_{t,p}^{12} \bar{P}_{t,p}^{MT,EPL} \end{aligned} \right) = \sum_{t=1}^{N_t} \left(\begin{aligned} & \pi_t^{E,EPL} P_{t,p}^{E,EPL} - a_{t,p}^{MT,EPL} P_{t,p}^{MT,EPL} - \\ & \delta_{ES,EPL} (P_{t,p}^{CH,ES} + P_{t,p}^{DCH,ES}) + \pi_t^{EV} P_{t,p}^{Ave,EVs} \end{aligned} \right) \quad (A11)$$

The nonlinear term $\pi_t^{E,EPL} P_{t,p}^{E,EPL}$ is obtained from (A11) and is used to linearize (2) as follows:

$$C_t^E = \pi_t^{E,Buy} P_t^{E,Buy} - \pi_t^{E,Sell} P_t^{E,Sell} + \sum_{p=1}^{N_p} \left[\begin{aligned} & -\eta_{t,p}^1 SoC_p^{EPL} + \eta_{t,p}^2 \bar{SoC}_p^{EPL} + \eta_{t,p}^4 \bar{P}_p^{CH,ES} \\ & + \eta_{t,p}^6 \bar{P}_p^{DCH,ES} + \eta_{t,p}^8 P_{t,p}^{Ave,EVs} + \eta_{t,p}^{10} \bar{P}_{t,p}^{E,EPL} \\ & + \eta_{t,p}^{12} \bar{P}_{t,p}^{MT,EPL} + a_{t,p}^{MT,EPL} P_{t,p}^{MT,EPL} \\ & - \pi_t^{EV} P_{t,p}^{Ave,EVs} + \delta_{ES,EPL} (P_{t,p}^{CH,ES} + P_{t,p}^{DCH,ES}) \end{aligned} \right] \quad \forall t \quad (A12)$$

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