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RESEARCH ARTICLE

A Second-Order Stochastic Dominance-Based Risk-Averse Strategy for Self-Scheduling of a Virtual Energy Hub in Multiple Energy Markets

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ABSTRACT Integrated energy systems are considered a practical solution to fulfill low-carbon energy systems. Accordingly, the concept of a virtual energy hub (VEH) and its capability to participate in different energy markets have attracted significant attention recently. In this regard, the self-scheduling problem of VEH, including a wide variety of uncertainties capable of participating in multiple energy markets, is addressed in this paper. To this end, a two-stage stochastic optimization has been implemented to solve the scheduling problem of a VEH equipped with renewable energy resources as well as conventional units as internal suppliers, different types of energy storage systems, hydrogen vehicles (HVs), and electric vehicles (EVs) in the intelligent parking lot (IPL). The studied VEH can participate in gas and hydrogen markets as well as day-ahead (DA) and real-time (RT) power and heat markets. The impact of flexible units, including energy storage systems and demand response programs, on the expected profit of the VEH is investigated accurately. Based on the obtained results employing a battery energy storage system (BESS), thermal energy storage system (TESS), hydrogen energy storage system (HESS), and cooling energy storage system (CESS) increases the profit of VEH by 0.88%, 0.62%, 1.5%, and 0.64%, respectively. Also, the profit of VEH can be increased by 1.02% and 0.25% by applying the electrical demand response program (EDRP) and thermal demand response program (TDRP), respectively. As risk management is critical for the participation of VEH in multiple energy markets, second-order-stochastic-dominance (SOSD) constraints are imposed on the scheduling problem instead of employing typical risk measures such as conditional value-at-risk (CVaR). Although the proposed risk-management method can shape optimal profit distribution based on the operators' attitude toward risk, benchmark selection is the main obstacle to the mentioned approach. To this end, the CVaR-based benchmark selection method is applied to overcome the stated obstacle and guarantee the problem's feasibility.

INDEX TERMS Integrated energy systems, virtual energy hub, multiple energy markets, second-order-stochastic-dominance risk-management method.

NOMENCLATURE

Acronyms

BESS	Battery Energy Storage System.
CESS	Cooling Energy Storage System.
ch	Charge.

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CHP	Combined Heat and Power.
CO_2	Carbon Dioxide.
CVaR	Conditional Value at Risk.
DA	Day-Ahead.
dch	Discharge.
ECH	Electric Chiller.
EDRP	Electric Demand Response Program.
EH	Energy Hub.
EHP	Electric Heat Pump.
GB	Gas Boiler.
H_2	Hydrogen.
HESS	Hydrogen Energy Storage System.
HPC	Hydrogen Producer Company.
HRS	Hydrogen Refueling Station.
HVs	Hydrogen Vehicles.
IGDT	Information Gap Decision Theory.
IPL	Intelligent Parking Lot.
Obj	Objective function.
P2H	Power to Hydrogen.
PDFs	Probability distribution functions.
PtX	Power-to-X.
PV	Photovoltaic System.
RES	Renewable Energy Sources.
RT	Real-Time.
ST	Solar Thermal .
TDRP	Thermal Demand Response Program.
TESS	Thermal Energy Storage System.
VEH	Virtual Energy Hub.
VPP	Virtual Power Plant.
WT	Wind Turbine.

Sets and Indices

$b \in B$	Set OF GBs.
$bs \in BS$	Set of BESS.
$ch \in CH$	Set of CHPs.
$cs \in CS$	Set of CESSs.
$ec \in EC$	Set of ECHs.
$ep \in EP$	Set of EHPs.
$hs \in HPC$	Set of HPCs.
$hs \in HS$	Set of HESSs.
$hy \in HY$	Set OF P2Hs.
$i \in I$	Set of EVs in IPL.
$p \in P$	Set of PVs.
$s \in S$	Set of Scenarios.
$st \in ST$	Set of STs.
$ts \in TS$	Set of TESSs.
$w \in W$	Set of WTs.

Parameters

$\eta_{BESS,dch}$, $\eta_{BESS,ch}$	Discharge/charge efficiency of BESSs.
η_B	Heat efficiency of Bs.
$\eta_{CESS,dch}$, $\eta_{CESS,ch}$	Discharge/charge efficiency of CESSs.
$\eta_{CHP,E}$, $\eta_{CHP,T}$	Electricity/heat efficiency of CHPs.
$\eta_{EVs,dch}$, $\eta_{EVs,ch}$	Discharge/charge efficiency of EVs in IPL.
$\eta_{HESS,dch}$, $\eta_{HESS,ch}$	Discharge/charge efficiency of HESSs.
$\eta_{TESS,ch}$, $\eta_{TESS,dch}$,$\eta_{TESS,sb}$	Charge/discharge/standby efficiency of TESSs.
λ_{DA}^{E}, λ_{DA}^{T}	DA electricity/heat price (cent/kWh).
λ_{EVs}^{con}	EVs charging price (cent/kWh).
λ_{gas}	Natural gas price (cent/kWh).
λ_{HPC}^{H}	Purchased price of hydrogen from HPC (cent/kWh).
λ_{P}^{E}, λ_{P}^{H}, λ_{P}^{T}	Sold price of electricity/hydrogen/heat, h).
$\lambda_{RT}^{E+}/\lambda_{RT}^{E-}$	RT purchased / sold electricity prices (cent/kWh).
$\lambda_{RT}^{T+}/\lambda_{RT}^{T-}$	RT purchased / sold heat prices (cent/kWh).
λ_{t}^{H}	Transportation Cost of Hydrogen (\$/km).
$\pi(s)$	Scenario probability.
$\underline{SoC}_{EVs}$, $\overline{SoC}_{EVs}$	energy stored in EVs of IPL (kWh).
$C_{CESS}^{ch,min}$, $C_{CESS}^{ch,max}$	Minimum/maximum charged cooling energy of CESSs (kW).
CP	EHPs' coefficient of performance.
Deg	Degradation cost of EVs' batteries.
E^{max} , T^{max}	The maximum percentage of participation in EDRP/ TDRP.
E_{BESS}^{min}, E_{BESS}^{max}	Minimum/maximum electrical energy stored in BESSs (kWh).
E_{CESS}^{min}, E_{CESS}^{max}	Minimum/maximum cooling energy stored in CESSs (kWh).
E_{demand}, T_{demand}	Electricity/ Heat demand .
E_{HESS}^{min}, E_{HESS}^{max}	Minimum/maximum Hydrogen stored in HESSs (kWh).
E_{max}^{grid} , T_{max}^{grid}	Maximum electricity / heat exchanged with network (kW).
E_{TESS}^{min}, E_{TESS}^{max}	Minimum/maximum thermal energy stored in TESSs (kWh).
H_{demand}, C_{demand}	Hydrogen/ Cooling demand .
$H_{HESS}^{ch,min}$, $H_{HESS}^{ch,max}$	Minimum/maximum charged hydrogen of HESSs (kW).
$H_{HESS}^{dch,min}$, $H_{HESS}^{dch,max}$	Minimum/maximum discharged hydrogen of HESSs (kW).
HPR	Heat-to-power ratio of CHPs.
MC_{CHP}	Maintenance cost of CHPs (cent/kWh).
N_{EVs}	Total number of EVs in IPL.
$P_{BESS}^{ch,min}$, $P_{BESS}^{ch,max}$	Minimum/maximum charged power of BESSs (kW).
$P_{BESS}^{dch,min}$, $P_{BESS}^{dch,max}$	Minimum/maximum discharged power of BESSs (kW).
P_{CH}^{min}, P_{CH}^{max}	Minimum/maximum generated power of CHPs (kW).

$P_{EVs}^{ch,max}$, $P_{EVs}^{dch,max}$	Maximum charged/discharged power of EVs in IPL (kW).
P_{PV}, P_{ST}	Generated power of PVs/ STs (kW).
P_{WT}	Generated power of WTs (kW).
q	The percent of same type of EVs.
RD_{CHP}, RU_{CHP}	Ramp-down/up ratio of CHPs (kW/h).
sd_{CHP}, su_{CHP}	Shout-down/start-up price of CHPs (cent).
SoC_{EVs}^{D}, SoC_{EVs}^{A}	Electrical energy stored of EVs in departure/arrival (kW).
T_{B}^{min}, T_{B}^{max}	Minimum/maximum generated heat of GBs (kW).
T_{EHP}^{min}, T_{EHP}^{max}	Minimum/maximum produced heat of EHPs (kW).
$T_{TESS}^{ch,min}$, $T_{TESS}^{ch,\max}$	Minimum/maximum charged heat of TESSs (kW).
$T_{TESS}^{dch,min}$, $T_{TESS}^{dch,max}$	Minimum/maximum discharged heat of TESSs (kW).

Decision Variables

δ,η	Auxiliary variables used to apply CVaR risk measure.
Ψ	Auxiliary variable used to apply SOSD constraints as risk management method.
C_{CESS}^{ch}, C_{CESS}^{dch}	Charged/discharged power of CESSs (kW).
C_{ECH}	Produced cooling by ECH (kW).
CR_{imb}^{E}, CR_{imb}^{T}	Cost/Revenue deviation between ged Energy with markets.
$CVaR$	Conditional Value at Risk ($).
E_{BESS}	Electrical energy stored in BESSs (kW).
E_{CESS}	Cooling energy stored in CESSs (kW).
$E_{demand,new}$	Electricity after applying EDRP (kW).
E_{DR}	Amount of shifted electrical load by EDRP (%).
E_{HESS}	Hydrogen energy stored in HESSs (kW).
E_{TESS}	Thermal energy stored in TESSs (kW).
G_{CH}, (G_{B}	Gas flow to CHPs/ Boilers (kW).
G_{T}	Gas flow from gas station (kW).
H_{HESS}^{ch}, H_{HESS}^{dch}	Charged/discharged power of HESSs (kWh).
H_{HPC}	Purchased hydrogen from HPC (cent/kWh).
H_{P2H}	Purchased hydrogen by P2H (kWh).
OC_{CHP}, OC_{B}	Operating cost of CHPs / boilers ($).
P_{BESS}^{ch}, P_{BESS}^{dch}	Charged/discharged power of BESSs (kW).
P_{CHP}	Generated power of CHPs (kW).
P_{EHP}, (P_{ECH}, (P_{P2H}	Consumed power of EHPs / ECHs/ P2Hs (kW).
P_{EVs}^{ch}, P_{EVs}^{dch}	Charged/discharged power of EVs in IPL (kW).
q_{DA}^{T}, q_{DA}^{E}	DA exchanged heat / power with et (kW).
q_{imb}^{T}, q_{imb}^{E}	Deviation between DA and RT power (kW).
q_{RT}^{T}, q_{RT}^{E}	RT exchanged heat / power with et (kW).
SoC_{EVs}	Electrical energy stored of EVs (kW).
T_{B}	Generated heat of GBs (kW).
T_{CHP}	Generated heat of CHPs (kW).
$T_{demand,new}$	Heat demand after applying TDRP (kW).
T_{DR}	Amount of shifted heat load by TDRP (%).
T_{EHP}	Generated heat of EHPs (kW).
T_{ST}	Output heat of STs (kW).
T_{TESS}^{ch}, T_{TESS}^{dch}	Charged/discharged heat of TESSs (kW).

Binary variables

$U_{.}$	Binary variable for the performance of.

I. INTRODUCTION

A. OVERVIEW AND MOTIVATIONS

Recently, the global concerns related to the energy crisis and air pollution have led to setting goals to reach net-zero carbon dioxide (CO2) societies. To this end, it is essential to utilize renewable energy sources (RES) as environmentally friendly methods to generate more power. Integrating different energy systems seems to be a practical approach toward increasing RES penetration while increasing the system's flexibility to address worldwide concerns. The concept of energy hub (EH) as an interface between different types of energy carriers is introduced, in which generation, consumption, storage, and transmission of various energy carriers are possible. On the other hand, the advent of new energy markets like the thermal energy market has stimulated EHs to participate in different energy markets to satisfy their various demands and maximize their profit. Meanwhile, the notion of virtual power (VPP), a set of aggregated distributed generators, electrical loads, and electrical energy storage capable of participating in power markets, and its combination with the EH concept draw significant attention. To this end, the concept of VEH is derived from VPP and EH concepts [1].So, the VEH, with self-scheduling methods, can participate in different energy markets to maximize its benefit [2].However, the uncertainties related to the different types of loads, energy market prices, and the presence of RES have led to complexity in the self-scheduling problem of the VEH. Thus, exploiting different kinds of energy storage systems and power-to-X (PtX) units, as well as participating in intraday energy markets, enable VEHs to compensate and control the extensive uncertainties close to real-time [3], [4].Therefore, addressing self-scheduling problem of VEH to participate in various energy markets considering a wide range of uncertainties is of great importance. In this paper, a two-stage stochastic programming method is utilized to deal with large amounts of uncertainties and enable the participation of VEH in the electricity, thermal, hydrogen, and gas market. Furthermore, a risk management method is used to prevent profit reductions based on the attitude of the VEH operator.

B. LITERATURE REVIEW

In this section, several related studies on the self-scheduling of VPPs are discussed in depth. A three-stage stochastic optimization problem is proposed [5] for the coordinated operation of a VPP, including a fleet of EVs as clients, a wind power producer, and a demand response aggregator, which participates in a three-settlement pool-based market to obtain maximum profit. A new VPP structure is defined in [6]by integrating power to gas technology and gas storage into a traditional VPP, including photovoltaic (PV), wind turbine (WT), EVs, and flexible loads, where a robust optimization theory and CVaR risk management are taken into account to propose a multi-objective scheduling method for the studied VPP. A novel approach for optimal management of a VPP integrating two levels of renewable energy is addressed in [7]. First, the scheduling of the VPP integrated with a wind farm and six hydroelectric power generations is done, where the produced electricity is directly injected into the distributed network. Second, on-site PV plants that prioritize self-consumption are considered in the structure of the VPP. The presented self-scheduling method of the studied VPP in [8] has enabled its participation in the day-ahead and reserve market by taking advantage of the storage capacity of EVs and wind power generators, where a new approach is presented to model uncertainties associated with EVs. In [9]], the scheduling problem of a VPP, including RESs, energy storage systems, and customers, is addressed to maximize its profit in multiple markets, in which the studied VPP can participate in DA, balance capacity, and intra-day electricity markets via formulating a two-stage chance-constrained optimization method. A two-stage chance-constrained distributionally robust optimization method is proposed in [10] for scheduling an EH in the DA and RT power market, DA gas, and carbon trading markets. In the first stage, the purchased energy cost from multiple energy markets is minimized, and in the second stage, the expected operation cost of the worst case is minimized. Also, the authors in [11] have proposed a two-stage stochastic model, which presents the operation of energy hubs in the presence of day-ahead and real-time electricity markets while taking into account the value-at-risk measure to manage the risk of high operation costs in worst scenarios. A two-stage risk-constrained energy scheduling method is proposed in [12] for an EH capable of trading electricity and thermal energies in both DA and RT stages. In this reference, the objective function is to maximize expected profit while minimizing the risk level. Moreover, the authors in [13] have proposed a scenario-based stochastic risk-based scheduling strategy for an EH that can participate in electricity and thermal markets as a consumer, where the objective function of the problem is to minimize the operation cost and risk associated with uncertainties. The corporation of the EH and VPP concepts has led to the introduction of the VEH concept, which can participate in different energy markets. A bi-level multi-objective scheduling framework for a VEH consisting of EVs and data centers in the presence of electricity and gas markets has been proposed [14]. In this reference, maximizing the profit of the VEH, minimizing carbon emissions, and mitigating the risk of uncertainties are among the main objectives of the scheduling problem. Also, the concept of VEH has been used for addressing the scheduling problem of the integrated electric-bus fast-charging station and intelligent parking lot (IPL) consisting of PV generation and battery energy storage systems (BESSs) in [15]. A cooperative three-stage decision-making strategy is proposed in this study to control the VEH capable of participating in the power market only. Notably, introducing local thermal markets contributes to evolving the concept of VEH. The robust self-scheduling of a VEH participating in both power and thermal DA and reserve markets is addressed [16], where the objective function of the problem is to maximize the total benefit of the VEH while minimizing pollutant emissions. A risk-constrained self-scheduling approach is presented in [1] for a VEH in the presence of both electrical and thermal markets to maximize its benefits, where the information gap decision theory (IGDT) method handles the decision-making problem under uncertainty and provides the risk management model. There are a variety of studies in which risk-management methods are applied to mitigate the risk of any deviation adversely from what is expected caused by uncertainty. The commonly used risk-management methods are value-at-risk (VaR) [17], [18], and conditional value at risk (CVaR) [19]. Since the VaR risk measure makes the optimization problems nonconvex, CVaR overweighs the VaR as a convex risk measure [17]. Also, stochastic dominance can be applied to stochastic optimization problems [20] as a risk-managing method to obtain optimal portfolio distribution based on the risk manager's attitude towards risk. The most prevalent forms of stochastic dominance are first and second orders. Applying first-order constraints to the optimization problems makes them non-convex; however, imposing second-order constraints keeps the optimization problem convex [21]. Therefore, SOSD constraints are used as a risk-managing method in optimization problems. In [22], a risk-averse two-stage stochastic optimization method employing different risk-management methods, including SOSD, is presented for optimal long-term generation expansion planning. However, the benchmark selection is not addressed. SOSD theory has been used in [23] to propose a risk-management approach for the bidding strategy of a wind producer in DA and RT markets. Furthermore, a decision-making framework based on SOSD has been proposed in [24] to introduce a risk-management approach for the bidding strategy of a wind producer in DA and RT markets. Furthermore, a decision-making framework based on SOSD has been proposed in [25]. At the same time, the SOSD approach is taken into account for risk-averse strategy. A multi-stage stochastic approach is adopted in [26] to provide investment and expansion strategies in the generating and storage capacities while long-term and short-term uncertainties are taken into account. SOSD constraints are utilized to limit the CO2 emissions in each planning strategy with the aim of minimizing total cost.

C. GAPS AND CONTRIBUTIONS

According to the literature review and Table 1, which gives a comparison between previous studies and the current study, although the importance of hydrogen for low-carbon energy systems is undeniable, HVs are not considered in the structure of studied VEH in reviewed papers. Moreover, the ability of the VEH to participate simultaneously in different energy markets is not addressed in any of investigated studies. Also, none of the studied papers have considered the risk management of the VEH scheduling by SOSD, which can directly determine the value of the worst scenario based on the preference of the operator. In some reviewed papers, SOSD constraints are imposed on the optimization problems; however, their benchmark selection method was not based on an appropriate method since some cases of benchmark selection will result in the infeasibility of the problem. This paper proposes a risk-averse self-scheduling model for a VEH to participate in different energy markets using SOSD as a risk-management method. Accordingly, the base contribution of this paper can be summarized as follow:

1) This study proposes a self-scheduling method for a VEH capable of participating in different energy markets, including power, thermal, hydrogen and gas.
2) A hydrogen refueling station (HRS) is considered to satisfy the hydrogen load of HVs
3) A risk-management method based on SOSD is applied to the model by determining the feasible benchmark selection region by CVaR risk measure, guaranteeing the feasibility of the problem.

II. PROBLEM DESCRIPTION

A. THE STRUCTURE OF VEH

The studied structure of the VEH is depicted in Fig. 1; as shown in this figure, the multi-energy demands of the VEH, including electricity, heat, hydrogen, and cooling, can be satisfied through the internal generation units of the VEH and multi-energy markets. Electrical demand corresponding to commercial, residential buildings, EVs, and internet data centers, which have become major power consumers in recent years, can be satisfied via combined heat and power (CHP) and renewable energy generators, such as WT, and PV, as internal generation of the VEH, and power markets. To reduce/increase power purchasing/selling at high market prices, consideration of BESS is of great importance. The cooling demand of VEH, consisting of the internet data center and buildings' cooling load, can be met by an electric chiller (ECH), which uses power to produce cooling. A cooling energy storage system (CESS) is also considered in the configuration of the VEH to take advantage of it. Also, thermal demand for commercial and residential buildings is satisfied by internal heat suppliers, including the gas boiler (GB), CHP, solar thermal (ST), and electric heat pump (EHP), which consume power to produce heat, and the participation of the VEH in thermal markets. Notably, TESS is also considered in the structure of the VEH. The hydrogen demand of the HVs can be satisfied in a hydrogen refueling station (HRS), in which hydrogen produced by the power to hydrogen (P2H) and hydrogen procured by a hydrogen producer company (HPC) can be utilized to satisfy hydrogen demand. A hydrogen energy storage system (HESS) is also taken into account in the structure of the VEH to store produced hydrogen by P2H to reduce power purchasing in market high prices. Since the VEH participates in various markets as a representative of all parts and is faced with market risk, it is essential to optimize its self-scheduling strategy to maximize revenue while considering the entire operational constraints.

Furthermore, the demands of end consumers of VEH are met with a stable retail energy price to provide consumers with a risk insulation strategy [27].

B. PROPOSED METHODOLOGY

The central goal of this study is to propose a decent approach for the optimal participation of a VEH in different energy markets. Thus, two-stage stochastic programming is applied to handle the decision-making problem under uncertainty. In this programming method, the first-stage decisions are known as here-and-now decisions, which are made before uncertainties are realized. The second-stage decisions are known as wait-and-see decisions, which are made after disclosing the uncertainties [28]. The inputs of the problem are reduced scenarios of electrical, thermal, cooling, and hydrogen loads, DA and RT electricity and thermal prices, and renewable power generation, including wind and solar. The outputs of the optimization problem are the submitted offers to exchange power and heat with DA markets, which are determined in the first stage of the problem. The RT obtained imbalanced cost or revenue relating to power and heat exchanged between VEH and RT heat and power markets and their differences with DA exchanged power and heat are determined in the second stage outputs. Also, the power dispatch of all generating and PtX units,

TABLE 1. Comparison between previous papers and present study.

Ref	Uncertainty management	DA local market trading: Electrical	Thermal	Hydrogen	Gas	Risk Measure	RT local market trading: Electrical	Thermal	DRP: EDRP	TDRP
[1]	IGDT	✓	✓	×	✓	IGDT	×	×	×	×
[10]	Two-stage Chance-Constrained Distributionally Robust	✓	×	×	✓	Robust Optimization	✓	×	×	×
[11]	Stochastic	✓	×	×	✓	Value-at-Risk	✓	×	×	×
[12]	Stochastic P-Robust	✓	✓	×	✓	Stochastic p-robust/CVaR/ Downside risk	✓	✓	×	×
[13]	Scenario-based Stochastic	✓	✓	×	✓	Downside risk	×	×	✓	✓
[14]	Robust-Stochastic	✓	×	×	✓	Robust optimization	×	×	✓	✓
[15]	Rolling-Optimization	✓	×	×	×	-	✓	×	×	×
This Study	Two-stage Stochastic Programming	✓	✓	✓	✓	SOSD approach using CVaR	✓	✓	✓	✓

BESS, TESS, HESS, CESS, and EVs' charging/discharging decisions, the amount of gas and hydrogen bought from the markets, and the shifted power and heat via electrical demand response programs (EDRPs) and thermal demand response programs (TDRPs) are determined in the second stage of the problem. As stochastic problems include a wide variety of uncertainties employing the risk-management method can mitigate the unfavorable effects of uncertainties. To this end, as SOSD risk-management method has privilege over other risk-management methods through achieving optimal distribution of the objective function, the constraints of this method applied to the problem. The CVaR risk measure was applied to the risk-neutral problem to obtain a feasible region for determining benchmarks. The proposed scheduling method is demonstrated in Fig. 2.

III. PROBLEM FORMULATION UNDER RISK-NEUTRAL STRATEGY

A. OBJECTIVE FUNCTION

The objective function of the self-scheduling problem of the VEH is to maximize its expected profit in the presence of different energy markets defined as follows: The difference between the income and expenditures of the VEH forms the expected profit. The total sold power and heat to DA and RT power and heat markets and sold power, heat, hydrogen, and cooling energy to customers form the income of the VEH. On the other hand, CHP unit's and boiler's operation costs, in addition to bought power and heat from DA and RT markets, form the expenditures. The first row in Eq. (1) represents the incomes/expenditures from DA exchanging power and heat with the upstream electricity and heat networks. The second row includes the RT power and heat imbalance costs or revenues. The third row represents the CHPs' and boilers' operation costs. The fourth and fifth rows are related to the income of the VEH from selling energy to customers. The fifth row ultimately formulates the revenue of the VEH from selling power to EVs. Besides, the EVs' battery degradation costs are also considered in the formulation. Finally, the costs of buying hydrogen from HPC and its transmission by trucks are included in the sixth row. As H2 transportation costs are varied between 1 to 5\$/km, the cost of H_2 transportation is considered 20 (\$) in this paper.

$$
\begin{aligned}
obj \\
&= \sum_t \sum_s \pi(s) \cdot \underbrace{\begin{bmatrix} \lambda_{DA}^{E}(t,s) \cdot q_{DA}^{E}(t) \\ +\lambda_{DA}^{T}(t,s) \cdot q_{DA}^{T}(t) \end{bmatrix}}_{1} \\
&- \underbrace{\begin{bmatrix} CR_{imb}^{E}(t,s) \\ +CR_{imb}^{T}(t,s) \end{bmatrix}}_{2} \\
&- \underbrace{\begin{bmatrix} \sum_{ch}^{CH} OC_{CHP}(ch,t,s) \\ +\sum_{b}^{B} OC_{B}(b,t,s) \end{bmatrix}}_{3} \\
&+ \underbrace{\begin{bmatrix} E_{demand,new}(t,s) \cdot \lambda_{P}^{E}(t) + \\ T_{demand,new}(t,s) \cdot \lambda_{P}^{T}(t) + \\ C_{demand}(t,s) \cdot \lambda_{P}^{T}(t) + \\ H_{demand}(t,s) \cdot \lambda_{P}^{H} \end{bmatrix}}_{4} \\
&+ \underbrace{\begin{bmatrix} N_{EVs} \cdot q(i) \cdot \\ (SoC_D(i,t,s) - SoC_A(i,t,s)) \cdot \lambda_{EVs}^{con} \\ +Deg \cdot P_{EVs}^{dch}(i,t,s) \end{bmatrix}}_{5} \\
&- \underbrace{\begin{bmatrix} \sum_t \sum_h H_{HPC}(h,t) \cdot \lambda_{HPC}^{H} + \\ H_{HPC}(h,t) \cdot \lambda_{t}^{H} \end{bmatrix}}_{6}
\end{aligned} \tag{1}
$$

B. ENERGY BALANCING CONSTRAINTS

The VEH's operator schedules the hourly power heat to participate in the DA markets as a producer or consumer.

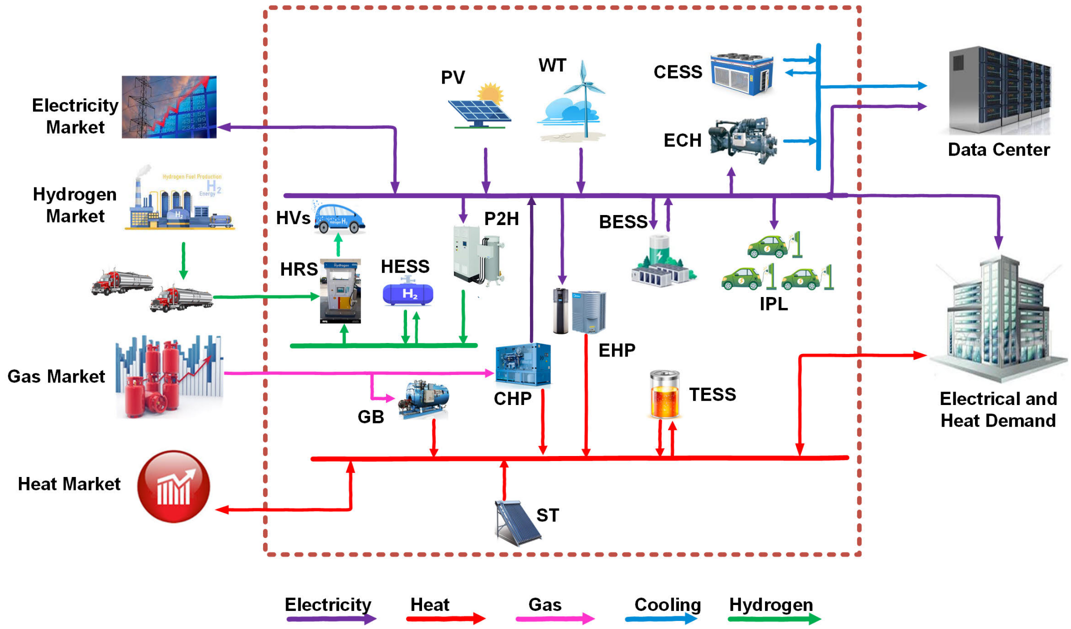

FIGURE 1. Detailed description of the studied VEH plan.

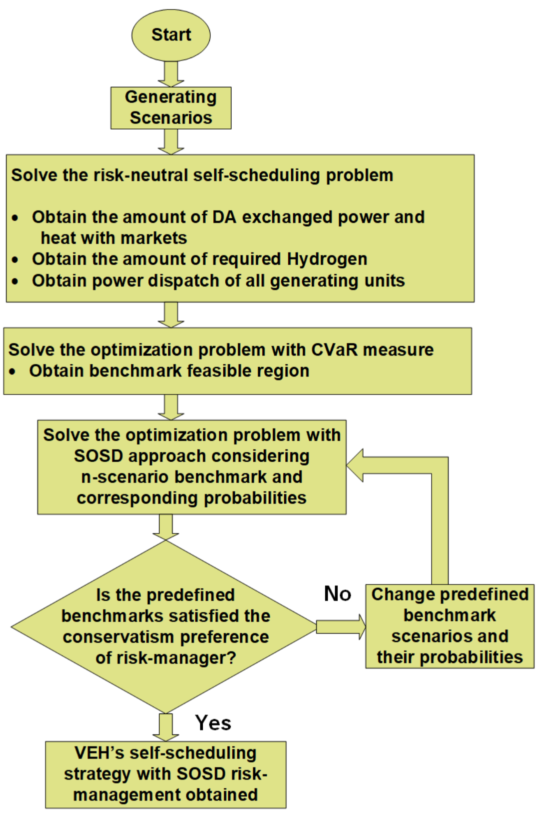

FIGURE 2. Solution algorithm of the presented the scheduling approach of the VEH.

Notably, the RT electricity and heat prices are calculated based on the DA electricity and heat market. Power and heat balance constraints are provided from Eq. (2)- Eq. (7). The amount of produced power and heat in the RT stage are provided through Eqs. (2) and (5). Since offers to DA power and heat markets are submitted a day before running RT markets, the differences between submitted offers to DA markets and the amount of produced power and heat in the RT stage are provided by Eqs. (3) and (6). In the case of shortage/surplus, the VEH has to buy/sell power and heat at higher/lower prices than the DA market prices by Eqs. (4) and (7). The cooling and hydrogen balance limitations are expressed by Eq. (8) and Eq. (9).

$$\begin{aligned} & q_{RT}^{E}(t,s) \\ & = \sum_{w=1}^{W} P_{WT}(w,t,s) + \sum_{p=1}^{P} P_{PV}(p,t,s) \\ & \quad + \sum_{ch=1}^{CH} P_{CHP}(ch,t,s) - \sum_{ec=1}^{EC} P_{ECH}(ec,t,s) \\ & \quad + \sum_{bs=1}^{BS} P_{BESS}^{dch}(bs,t,s) \\ & \quad + \sum_{i=1}^{I} N_{EVs}(i)\cdot q(i)\cdot P_{EVs}^{dch}(i,t,s) \\ & \quad - \sum_{hy=1}^{HY} P_{P2H}(hy,t,s) - \sum_{ep=1}^{EP} P_{EHP}(ep,t,s) \\ & \quad - \sum_{bs=1}^{BS} P_{BESS}^{ch}(bs,t,s) - E_{demand,new}(t,s) \\ & \quad - \sum_{i=1}^{I} N_{EVs}(i)\cdot q(i)\cdot P_{EVs}^{ch}(i,t,s) \end{aligned} \tag{2}$$

$$q_{imb}^{E}(t,s) = q_{DA}^{E}(t,s) - q_{RT}^{E}(t,s) \tag{3}$$

$$CR_{imb}^{E}(t,s) = \begin{cases} q_{imb}^{E}(t)\cdot\lambda_{RT}^{E+}, & \text{if } q_{imb}^{E}(t)>0 \\ q_{imb}^{E}(t)\cdot\lambda_{RT}^{E-}, & \text{if } q_{imb}^{E}(t)<0 \end{cases} \tag{4}$$

$$q_{RT}^{T}(t,s) = \sum_{c=1}^{C} T_{CHP}(ch,t,s) + \sum_{hp=1}^{HP} T_{EHP}(ep,t,s) + \sum_{b=1}^{B} T_{B}(b,t,s) + \sum_{st=1}^{ST} T_{ST}(st,t,s) + \sum_{ts=1}^{TS} T_{TESS}^{dch}(ts,t,s) - \sum_{ts=1}^{TS} T_{TESS}^{ch}(ts,t,s) - T_{demand,new}(t,s) \tag{5}$$

$$q_{imb}^{T}(t,s) = q_{DA}^{T}(t,s) - q_{RT}^{T}(t,s) \tag{6}$$

$$CR_{imb}^{T}(t,s) = \begin{cases} q_{imb}^{T}(t)\cdot\lambda_{RT}^{T+}, & \text{if } q_{imb}^{T}(t)>0 \\ q_{imb}^{T}(t)\cdot\lambda_{RT}^{T-}, & \text{if } q_{imb}^{T}(t)<0 \end{cases} \tag{7}$$

$$C_{demand}(t,s) + C_{CESS}^{ch}(cs,t,s) = C_{CESS}^{dch}(cs,t,s) + C_{ECH}(ec,t,s) \tag{8}$$

$$H_{demand}(t,s) + H_{HESS}^{ch}(hs,t,s) = H_{HPC}(h,t) + H_{P2H}(hy,t,s) + H_{HESS}^{dch}(hs,t,s) \tag{9}$$

C. EXCHANGED POWER AND HEAT

The DA and RT exchanged power and heat of the VEH with the electricity and heat markets are limited by Eqs. (10) and (11), respectively.

$$-E_{grid}^{\max} \le q_{DA}^{E}(t) - q_{imb}^{E}(t,s) \le E_{grid}^{\max} \tag{10}$$

$$-T_{grid}^{\max} \le q_{DA}^{T}(t) - q_{imb}^{T}(t,s) \le T_{grid}^{\max} \tag{11}$$

D. GAS FLOW CONSTRAINTS

The required gas for the operation of CHP and boiler is the total amount of gas flow purchased from the gas station, which is shown in Eq. (12).

$$G_{T}(t,s) = G_{CHP}(ch,t,s) + G_{Boiler}(b,t,s) \tag{12}$$

E. CHP

CHP units are mathematically formulated by Eqs. (13)-(20). Their required fuel is calculated by Eq. (13). Also, the costs related to startup and shutdown states of the CHP plants are expressed by Eqs. (14) and (15), respectively. Notably, the electrical and thermal generations of CHP units are formulated by Eq. (16) and Eq. (17), which are interdependent. The performance status of the CHP units is defined by a binary variable, which is equal to 0 if each of the CHP units is in the off state and 1 otherwise. The ramp-up and ramp-down constraints of CHP units are expressed in Eqs. (18) and (19). Finally, the operation cost of CHP units is formulated through Eq. (20).

$$G_{CH}(ch,t,s) = \frac{P_{CH}(ch,t,s)}{HV_{gas}\cdot\eta_{CH-E}(ch)} \tag{13}$$

$$0 \le SUC_{CHP}(ch,t,s) = su_{CHP}(ch)\cdot\begin{pmatrix} U_{CHP}(ch,t,s)- \\ U_{CHP}(ch,t-1,s) \end{pmatrix} \tag{14}$$

$$0 \le SDC_{CHP}(ch,t,s) = sd_{CHP}(ch)\cdot\begin{pmatrix} U_{CHP}(ch,t-1,s) \\ -U_{CHP}(ch,t,s) \end{pmatrix} \tag{15}$$

$$T_{CHP}(ch,t,s) \le P_{CHP}(ch,t,s)\cdot HPR(ch)\cdot\eta_{CHP-T}(ch) \tag{16}$$

$$T_{CHP}(ch,t,s) \le P_{CHP}(ch,t,s)\cdot HPR(ch)\cdot\eta_{CHP-T}(ch) \tag{17}$$

$$T_{CHP}(ch,t,s) - T_{CHP}(ch,t-1,s) \le RU_{CHP}(ch)\cdot U_{CHP}(ch,t,s) \tag{18}$$

$$T_{CHP}(ch,t-1,s) - T_{CHP}(ch,t,s) \le RD_{CHP}(ch)\cdot U_{CHP}(ch,t,s) \tag{19}$$

$$OC_{CHP}(ch,t,s) = G_{CHP}(ch,t,s)\cdot\lambda_{gas} + P_{CHP}(ch,t,s)\cdot MC_{CHP} + SUC_{CHP}(ch,t,s) + SDC_{CHP}(ch,t,s) \tag{20}$$

F. BOILER

The boiler units' operation costs are formulated as shown in Eq. (21). The amount of gas required by boilers is formulated by Eq. (22). Also, the outputs of the boiler units are limited by Eq. (23). [29]

$$OC_{B}(b,t,s) = G_{B}(b,t,s)\cdot\lambda_{gas} \tag{21}$$

$$G_{B}(b,t,s) = \frac{T_{B}(b,t,c)}{HV_{gas}\cdot\eta_{B}(b)} \tag{22}$$

$$T_{B}^{\min} \le T_{B}(b,t,s) \le T_{B}^{\max} \tag{23}$$

G. EHP

EHP units consume electricity to produce heat, as shown in Eq. (24). Furthermore, the produced heat of EHPs are limited by Eq. (25) [30]

$$T_{EHP}(ep,t,s) = P_{EHP}(ep,t,s)\cdot CP(ep) \tag{24}$$

$$T_{EHP}^{\min}(ep) \le T_{EHP}(ep,t,s) \le T_{EHP}^{\max}(ep) \tag{25}$$

H. BESS

The technical constraints of BESSs are formulated in Eqs (26)-(30). Charged and discharged power of these units is limited by Eqs. (26) and (27), respectively. A binary variable is used to define the charge and discharge status of these units and to avoid their simultaneous charge and discharge. Furthermore, Eqs. (28), and (29) are provided to model the capacity limitation of BESSs. Finally, the amount of stored electrical energy is calculated by Eq (30).

$$0 \le P_{BESS}^{ch}(bs,t,s) \le P_{BESS}^{ch,\max}(bs).\left(U_{BESS}(bs,t,s)\right) \tag{26}$$

$$\begin{aligned}0 &\leq P^{dch}_{BESS}(bs,t,s)\\ &\leq P^{dch,\max}_{BESS}(bs).\left(1-U_{BESS}(bs,t,s)\right)\end{aligned}\tag{27}$$

$$E^{\min}_{BESS}(bs) \leq E_{BESS}(bs,t,s) \leq E^{\max}_{BESS}(bs)\tag{28}$$

$$E_{BESS}(bs,t,s) = E^{\min}_{BESS}(bs)\tag{29}$$

$$\begin{aligned}E_{BESS}(bs,t,s) &= E_{BESS}(bs,t-1,s)\\ &+ P^{ch}_{BESS}(bs,t,s)\cdot\eta_{BESS-ch}(bs)\\ &- P^{dch}_{BESS}(bs,t,s)/\eta_{BESS-dch}(bs)\end{aligned}\tag{30}$$

It is worth mentioning that the technical constraints of HESS and CESS are formulated similarly

I. TESS

Similar to BESS units, the technical constraints of the TESSs are formulated in Eqs (31)-(34). The charge and discharge status of these units are defined by a binary variable, avoiding simultaneous charging, and discharging of the TESSs. Also, the capacity limitation of the TESSs is expressed via Eq. (33). Finally, Eq. (34) is stated the amount of thermal energy stored in TESSs [31]

$$\begin{aligned}0 &\leq T^{ch}_{TESS}(ts,t,s)\\ &\leq T^{ch,\max}_{TESS}(ts)\cdot\left(U_{TESS}(ts,t,s)\right)\end{aligned}\tag{31}$$

$$\begin{aligned}0 &\leq T^{dch}_{TESS}(ts,t,s)\\ &\leq T^{dch,\max}_{TESS}(ts)\cdot\left(1-U_{TESS}(ts,t,s)\right)\end{aligned}\tag{32}$$

$$E^{\min}_{TESS}(ts) \leq E_{TESS}(ts,t,s) \leq E^{\max}_{TESS}(ts)\tag{33}$$

$$\begin{aligned}&E_{TESS}(ts,t,s)\\ &\quad= E_{TESS}(ts,t-1,s)\cdot\eta_{TESS-sb}(ts)\\ &\quad+ T^{ch}_{TESS}(ts,t,s)\cdot\eta_{TESS-ch}(ts)\\ &\quad- T^{dch}_{TESS}(ts,t,s)/\eta_{TESS-dch}(ts)\end{aligned}\tag{34}$$

J. EDRP AND TDRP

Demand-side management can have noticeable impacts on energy management. Accordingly, mathematical formulation of EDRPs and TDRPs are imposed on the model via Eqs. (35)-(40) [13], [32]. Time-of-use demand response programs are utilized to shift a predefined percentage of peak-load time periods to off-peak periods.

$$E_{demand,new}(t,s) = E_{demand}(t,s) + E_{DR}(t,s)\tag{35}$$

$$\begin{aligned}&- E^{\max}\cdot E_{demand}(t,s)\\ &\leq E_{DR}(t,s) \leq E^{\max}\cdot E_{demand}(t,s)\end{aligned}\tag{36}$$

$$\sum_{t=1}^{24} E_{DR}(t,s) = 0\tag{37}$$

$$T_{demand,new}(t,s) = T_{demand}(t,s) + T_{DR}(t,s)\tag{38}$$

$$\begin{aligned}&q - T^{\max}\cdot T_{demand}(t,s)\\ &\leq T_{DR}(t,s) \leq T^{\max}\cdot T_{demand}(t,s)\end{aligned}\tag{39}$$

$$\sum_{t=1}^{24} T_{DR}(t,s) = 0\tag{40}$$

As Eqs. (35) and (38) show, the new electrical and thermal load after implementation of EDRPs and TDRPs are equal to the base electrical and thermal load plus the determined shifted amount, which is specified in Eqs. (36) and (39). It is notable that the total amount of decreased or increased electrical and heat load should be equal to zero, as shown in Eqs (37) and (40).

K. ECH

ECHs can be considered as PtX units since these units consume electricity to produce cooling energy. Mathematical formulations of ECHs are expressed as follows:

$$C_{ECH}(ec,t,s) = P_{ECH}(ec,t,s)\cdot\eta_{ECH}\tag{41}$$

$$C^{\min}_{ECH}(ec) \leq C_{ECH}(ec,t,s) \leq C^{\max}_{ECH}(ec)\tag{42}$$

L. P2H

The mathematical formulation of P2Hs as other PtX units consuming power to produce hydrogen employed in the structure of the studied VEH can be expressed as follows:

$$H_{P2H}(hy,t,s) = P_{P2H}(hy,t,s)\cdot\eta_{P2H}\tag{43}$$

$$H^{\min}_{P2H} \leq H_{P2H}(ec,t,s) \leq H^{\max}_{P2H}\tag{44}$$

M. IPL

Available EVs in the IPL provide the operator with extra degrees of freedom in decision-making since the operator can exploit the stored power on the EVs while participating in electricity markets. Hence, the amount of stored power in the EVs is formulated through Eq. (45). Also, the limitations of power charging and discharging of the present EVs in the IPL are expressed in Eqs. (46) and (47). Furthermore, constraint (48) is utilized to avoid charging and discharging EVs at the same time. Finally, Eqs. (49) and (50) express the limitations of stored electricity [33].

$$\begin{aligned}SoC_{EVs}(i,t,s) &= SoC_{EVs}(i,t-1,s)\\ &+ P^{ch}_{EVs}(i,t,s)\cdot\eta_{EVs-ch}\\ &- P^{dch}_{EVs}(i,t,s)/\eta_{EVs-dch}\end{aligned}\tag{45}$$

$$\begin{aligned}&P^{ch}_{EVs}(i,t,s)\\ &\quad\leq \bar{P}^{ch}_{EVs}(i)\cdot U_{EVs,ch}(i,t,s)\end{aligned}\tag{46}$$

$$\begin{aligned}&P^{dch}_{EVs}(i,t,s)\\ &\quad\leq \bar{P}^{dch}_{EVs}(i)\cdot U_{EVs,dch}(i,t,s)\end{aligned}\tag{47}$$

$$U_{EVs,ch}(i,t,s) + U_{EVs,dch}(i,t,s) \leq 1\tag{48}$$

$$\underline{SoC}_{EVs}(i) \leq SoC_{EVs}(i,t,s) \leq \overline{SoC}_{EVs}(i)\tag{49}$$

$$SoC^{D}_{EVs}(i,t,s) = \overline{SoC}_{EVs}(i)\tag{50}$$

It is worth noting that, based on generated scenarios for solar radiation and wind speed, the output power of PVs, STs, and WTs are calculated by expressions provided in [2] and [24].

IV. PROBLEM FORMULATION UNDER RISK-AVERSE STRATEGY

The presence of extensive uncertainties in the self-scheduling problem of the VEH has inevitably influenced the expected profit of the VEH. However, in such problems, optimizing the expected value while ignoring other parameters, such as the distribution of the objective function, can bring high risk to the operator. For instance, the optimal distribution of an objective function with a high expected value may have an unacceptable value in the worst scenario [34]. Employing the best risk management approach is very important to avoid the unfavorable effects of uncertainties. Particularly, in stochastic-based optimization problems, since the impacts of unacceptable scenarios cannot be controlled without applying risk-management methods, different methods are used to hedge against unacceptable scenarios. Accordingly, there are several studies that apply risk-management methods to the scheduling problem. Some scheduling problems use robust optimization and the IGDT method to change the conservatism level of the operator and, in this way, manage the risk of decision-making under uncertainty. In some papers, risk-managing measures like CVaR, as the most common risk measure, are applied to the objective function of the optimization problem to obtain a trade-off between expected profit and the risk of the profit. In addition, stochastic dominance as a mathematical approach can be used for risk-management of decision-making problems under uncertainty by adding related constraints to the optimization problem. Second-order stochastic dominance (SOSD) is an approach that forces the optimal distribution objective function to exceed a predetermined benchmark distribution, which is defined by the preference of the risk manager [35]. Adding the SOSD constraints to the problem, the risk manager can manage risk while obtaining an optimal portfolio. However, the applicability of an appropriate benchmark selection method is a controversial task due to any unfeasibility caused by benchmark selection. Notably, imposing the CVaR risk measure on the optimization problem can improve the expected profit in the worst scenario while decreasing the amount of the expected profit in the best scenario. However, the amount of profit improvement in the worst scenario cannot be determined by applying the CVaR risk measure to the problem. It is worth noting that imposing SOSD constraints can directly define the amount of expected profit in the worst scenario based on the preference of the operator. So, in this paper, rather than using the CVaR measure, SOSD constraints are added to the optimization problem for risk management.

A. RISK-AVERSE SCHEDULING OF THE VEH WITH CVAR

Due to performance feathers and mathematical characteristics, CVaR is the most applicable risk measure in electricity markets [36]. The objective function of the risk-averse problem incorporated CVaR metric is maximizing the expected profit and CVaR, which is shown in Eq. (51), in which the conservatism level of the operator is determined by. Applying the risk-management method with CVaR in the risk-neutral scheduling of the VEH model is expressed as follows:

$$Maximize(1-\beta)\cdot Obj+\beta\cdot CVaR \tag{51}$$

CVaR metric is defined by Eq. (52). For a specified, determines and controls the trade-off between risk measure and expected profit (i.e., objective function) [36]. Moreover, Eqs. (53) and (54) determines the difference between the expected profit of each scenario and CVaR if the difference is positive; otherwise, it is considered zero [37].

$$CVaR=\delta-\frac{1}{1-\alpha}\cdot\sum_{s}^{S}\pi\left(s\right)\cdot\eta\left(s\right) \tag{52}$$

$$\delta-obj(s)\leq\eta\left(s\right) \tag{53}$$

$$\eta\left(s\right)\geq 0 \tag{54}$$

B. RISK-AVERSE SCHEDULING OF THE VEH WITH SOSD

In this risk-management method, nothing is incorporated with the objective function, and just SOSD constraints are added as constraints to the model. The predefined benchmarks imposed on the model are based on the risk attitude of the operator of the VEH to ensure the optimal profit distribution dominates the predetermined benchmark distribution, which can be defined by a number of scenarios and their corresponding probabilities. Each scenario is determined by two factors, including a predetermined value k(v) or k(v) and a probability (v) or (v). Solving the self-scheduling problem considering SOSD constraints results in obtaining optimal profit distribution while dominating predefined benchmark distribution. The constraints are expressed as follows [36]:

$$k\left(v\right)-\begin{bmatrix}+\left[\lambda_{DA}^{E}\left(t,s\right)\cdot q_{DA}^{E}\left(t\right)+\lambda_{DA}^{T}\left(t,s\right)\cdot q_{DA}^{T}\left(t\right)\right]\\-\left[CR_{imb}^{E}\left(t,s\right)+CR_{imb}^{T}\left(t,s\right)\right]\\-\left[\sum_{ch}^{CH}OC_{CHP}(ch,t,s)+\sum_{b}^{B}OC_{GB}(b,t,s)\right]\\+\begin{bmatrix}ED_{new}(t,s)\cdot\lambda_{P}^{E}\left(t\right)\\+TD_{new}\left(t,s\right)\cdot\lambda_{P}^{T}\left(t\right)\\+CD(t,s)\cdot\lambda_{P}^{T}\left(t\right)\\+HD(t,s)\cdot\lambda_{P}^{H}\end{bmatrix}\\+\begin{bmatrix}N_{EVs}\cdot q(i)\cdot\begin{pmatrix}SoC_{D}\left(i,t,s\right)\\-SoC_{A}\left(i,t,s\right)\end{pmatrix}\cdot\lambda_{EVs}^{con}\\+Deg\cdot P_{EVs}^{dch}\left(i,t,s\right)\end{bmatrix}\\-\begin{bmatrix}\sum_{h}H_{HPC}\left(h,t\right)\cdot\lambda_{HPC}^{H}\\+H_{HPC}\left(h,t\right)\cdot\lambda_{t}^{H}\end{bmatrix}\end{bmatrix}\leq\Psi(s,v) \tag{55}$$

$$\sum_{s}\pi(s).\Psi(s,v)\leq\sum_{v'}\tau\left(v'\right).\max(k(v)-k(v'),0) \tag{56}$$

$$\Psi(s,v)\geq 0 \tag{57}$$

V. INPUT DATA

The uncertain nature of stochastic parameters is considered in the problem through their probability distribution functions (PDFs) to produce the desired number of scenarios. The

TABLE 2. Probabilities of each reduced scenario.

Scenarios	S_1	S_2	S_3	S_4	S_5
Probability	0.159	0.113	0.101	0.094	0.083
Scenarios	S_6	S_7	S_8	S_9	S_{10}
Probability	0.07	0.071	0.075	0.123	0.111

TABLE 3. Technical characteristics of VEH's components.

CHP			
P^{max}_{CHP} 800 (kW)	P^{min}_{CHP} 50 (kW)	η_{CHP-E} 0.3	η_{CHP-H} 0.45
HPR 1			
sd_{CHP} 2.5 (cent)	su_{CHP} 2.5 (cent)	RD_{CHP} 50(kW/h)	RU_{CHP} 50(kW/h)
MC_{CHP} 1.6 (cent/kWh)			
GB			
H^{max}_{B} 500 (kW)	H^{min}_{B} 50 (kW)	η_{B} 0.9	
WTs			
V^{ci}_{WT} 5(m/s)	V^{Rated}_{WT} 14(m/s)	V^{CO}_{WT} 25(m/s)	P^{max}_{WT} 1500(KW)
ST		PV	
A_{ST} 5(m/s)	η_{ST} 14(m/s)	A_{PV} 25(m/s)	η_{PV} 1500(KW)

Weibull and Beta PDFs are utilized for generating wind speed and solar irradiation scenarios, respectively [38]. Also, normal PDF obtained from historical data is utilized to generate market prices and power/heat/hydrogen/cooling demand scenarios [13]. Then, generated scenarios are reduced to ten scenarios via the fast backward/forward reduction method provided with the SCENRED tool in the GAMS software to decrease the computational burden and complexity imposed on the problem by a large number of produced scenarios. The probability of each reduced scenario is provided in Table 2. Before analyzing the results, the input data of the studied system is introduced in this section. Accordingly, the studied VEH comprises CHPs, GBs, WTs, STs, and PVs, which their specifications are provided in Table 3. Also, the characteristics of the PtX and energy storage systems are reported in Tables 4 and 5, respectively. Furthermore, the specification of different types of EVs and their characteristics in different scenarios are provided in Table 6 and Table 7, respectively. Accordingly, wind speed reduced scenarios are depicted in Fig. 3. The reduced scenarios of the Solar irradiance are provided in Fig. 4. Also, electrical, thermal, hydrogen, and cooling demands reduced scenarios are provided in Fig 5, 6, 7, and 8, respectively. Reduced scenarios of the DA electricity and heat market prices are provided in Fig 9 and 10, respectively.

VI. RESULTS AND DISCUSSION

The proposed model is a mixed-integer linear programming problem, which is implemented in the general algebraic modeling system (GAMS) software, CPLEX solver. A computer

TABLE 4. Technical characteristics of VEH's PtX systems.

EHP		
H^{max}_{EHP} 500 (kW)	H^{min}_{EHP} 0	CP_{EHP} 2.5
ECH		
C^{max}_{ECH} 300	C^{min}_{ECH} 0	CP_{ECH} 4
P2H		
H^{max}_{P2H} 150	H^{min}_{P2H} 0	CP_{P2H} 0.8

TABLE 5. Technical characteristics of VEH's energy storage systems.

BESS	
$E^{max}_{BESS}, E^{min}_{BESS}$ 1000,200 (kWh)	$P^{ch,max}_{BESS}, P^{ch,min}_{BESS}$ 200,0 (kW)
$P^{dch,max}_{BESS}, P^{dch,min}_{BESS}$ 200,0(kW)	$\eta_{BESS-ch}, \eta_{BESS-dch}$ 0.98,0.98
TESS	
$E^{max}_{TESS}, E^{min}_{TESS}$ 1000,50(kWh)	$T^{ch,max}_{TESS}, T^{ch,min}_{TESS}$ 200,0(kW)
$T^{dch,max}_{TESS}, T^{dch,min}_{TESS}$ 200,0(kW)	$\eta_{TESS-ch}, \eta_{TESS-dch}, \eta_{TESS-sb}$ 1,1,1
HESS	
$E^{max}_{HESS}, E^{min}_{BESS}$ 200,0(kWh)	$H^{ch,max}_{BESS}, H^{ch,min}_{BESS}$ 50,0(kW)
$H^{dch,max}_{BESS}, H^{dch,min}_{BESS}$ 50,0(kW)	$\eta_{HESS-ch}, \eta_{HESS-dch}$ 0.99,0.99
CESS	
$E^{max}_{CESS}, E^{min}_{CESS}$ 1000,50(kWh)	$C^{ch,max}_{CESS}, C^{ch,min}_{CESS}$ 200,0(kW)
$C^{dch,max}_{CESS}, C^{dch,min}_{CESS}$ 200,0(kW)	$\eta_{CESS-ch}, \eta_{CESS-dch}$ 0.98,0.98

TABLE 6. Characteristics of different types of EVs.

EV Type	V_1	V_2	V_3	V_4	V_5
$P^{max}_{i,ch}(kW)$	17.2	17.2	20	11.5	12.5
$P^{max}_{i,dch}(kW)$	17.2	17.2	20	11.5	12.5
Percentage(%)	21.81	18.64	15	25.52	19.3
$P^{min}_{i,ch}(kW)$	3.2	3.2	5	1.5	2.5
$P^{min}_{i,dch}(kW)$	3.2	3.2	5	1.5	2.5
capacity (kWh)	100	100	41	40	25

with 16 GB RAM and Intel Core i7-7700HQ CPU (2.80-GHz) is used for the simulation.

A. RISK-NEUTRAL SCHEDULING OF THE VEH

In this part, the risk-neutral scheduling of the VEH is addressed. The results of this section are divided into four parts: electricity, thermal, cooling, and hydrogen analysis.

TABLE 7. Characteristics of EVS in the different scenarios.

Scenarios	At	Dt	SOC_A	SOC_A
S_1	5	20	0.58	0.89
S_2	7	17	0.57	0.93
S_3	6	22	0.22	0.9
S_4	5	19	0.5	0.92
S_5	9	20	0.20	0.89
S_6	5	22	0.12	0.97
S_7	6	17	0.34	0.82
S_8	8	22	0.42	0.9
S_9	11	18	0.69	0.87
S_{10}	7	18	0.24	0.95

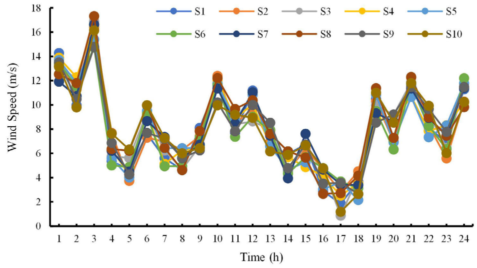

FIGURE 3. Reduced scenarios of the wind speed.

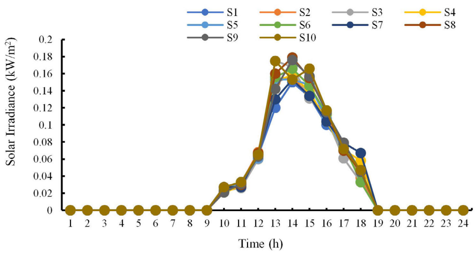

FIGURE 4. Reduced scenarios of the solar irradiance.

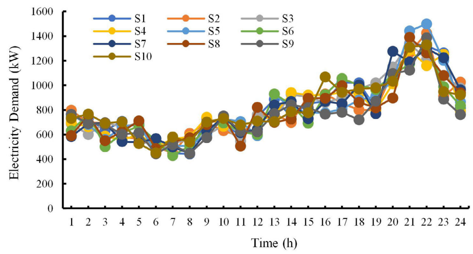

FIGURE 5. Reduced scenarios of the Electrical load.

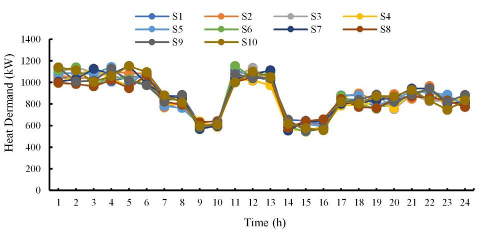

FIGURE 6. Reduced scenarios of the heat load.

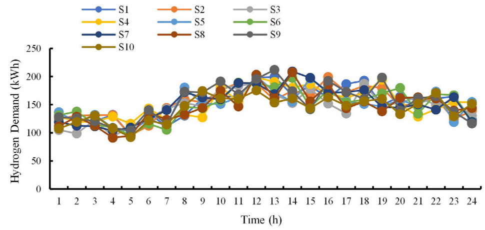

FIGURE 7. Reduced scenarios of the hydrogen load.

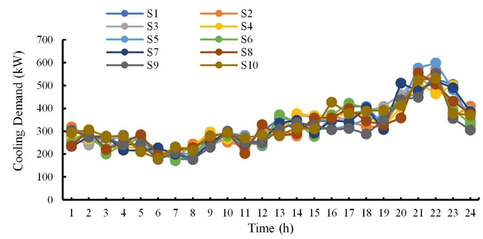

FIGURE 8. Reduced scenarios of the cooling load.

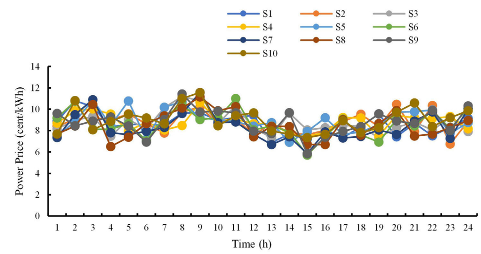

FIGURE 9. Reduced scenarios of the DA electricity market prices.

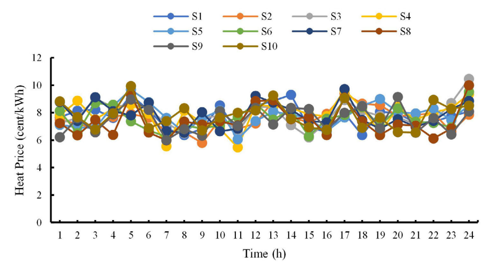

FIGURE 10. DA Heat market prices' reduced scenarios.

1) ELECTRICITY ANALYSIS

At first, the performance of the studied VEH at the RT stage is evaluated. To this end, the expected values of the electrical generation units of the system consisting of WT, PV, CHP, power storages including EVs and BESS, PtX units including EHP, ECH, and P2H, as well as electrical demand are analyzed in more detail in Fig 11. Notably, power generations/ consumptions are depicted above/below the horizontal axis. Also, sold/purchased power to/from the upstream grid is shown below/above the horizontal axis. Accordingly, the VEH participates in the electricity market as an energy producer at some hours (t = 1-12), and as a consumer during some hours (t = 13-24). Therefore, the operator of the VEH decides to charge the energy storage systems during low energy prices to reduce electricity purchasing from the grid or even increase electricity selling to the market during high electricity prices. To this end,

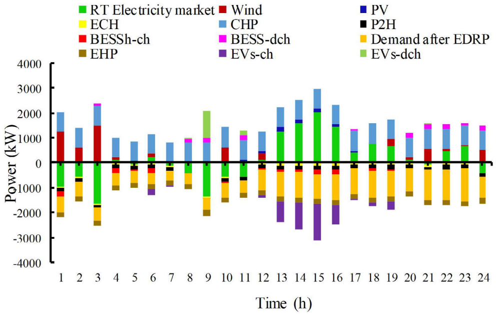

FIGURE 11. Electricity balance.

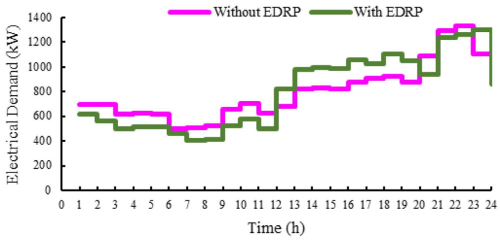

FIGURE 12. The impact of EDRP on the electricity load.

BESS is charged during off-peak hours (t = 12-16) and discharged during hours (t = 20-24). Similarly, EVs in the IPL are charged (t = 12-19) during low electricity prices and discharged (t = 9, 11) to enable the participation of the VEH as a power producer in the market.

In Fig. 12., the impact of imposing EDRP is demonstrated on the electrical demand. Accordingly, applying EDRP leads to shifting electrical demand from peak electricity-market prices hours (1 -12) to off-peak electricity prices
hours (13)-(19).

The impacts of employing EDRP and BESS on the DA exchanged power of the VEH with the market are demonstrated in Fig. 13. Notably, the purchased/sold power from/to the upstream grid is shown below/above the horizontal axis. The presence of flexible units can increase the amount of sold energy to the grid (t = 3, 8, 9) at the peak electricity price. Also, it enables VEH to buy more electricity from the grid at low electricity price hours (t = 13-20). The revenue of the participation of VEH in the DA and RT electricity market increases by 0.88% and 1.02% by employing the BESS and EDRP, respectively. Notably, the considered VEH can take or lose profit by participating in the RT electricity market. Therefore, in this part, the influence of implementing flexible resources, including BESS and EDRP, is investigated on the VEH obtained profit/loss in the RT stage. To this end, the expected profit or loss resulting from the participation of the VEH in the RT electricity market, in the presence and absence of flexible units, is provided in Table 8 for every hour of the studied day. It should be mentioned that in this table, obtained results of imbalanced cost and revenue of every scenario and their probabilities are considered to calculate the expected imbalanced cost or revenue of each hour. It is worth

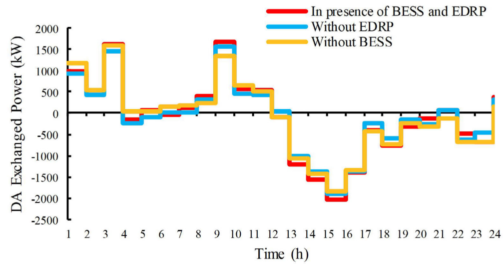

FIGURE 13. The impact of employing BESS and EDRP on the VEH's exchanged power with DA electricity market.

TABLE 8. Imbalanced power cost/revenue in every hour of a studied day.

Time (h)	In the presence of BESS and EDRP	Without BESS in the presence of EDRP	Without BESS in the presence of BESS
1	-263.99	-442.01	-288.97
2	42.82	-47.74	-178.37
3	178.97	371.77	-144.96
4	210.79	255.59	179.6
5	168.39	268.38	364.57
6	-1279.42	-1585.23	-1274.3
7	0	0	-46.21
8	-49.43	-77.18	-108.85
9	-3398.31	-3561.64	-2958.42
10	-131.22	-229.98	-660.1
11	199.53	175.56	-96.5
12	37	36.26	148.67
13	-347.36	-480.74	-76.84
14	-80.89	-79.88	106.85
15	-91.81	-38.65	-91.81
16	-290.61	-405.18	-299.68
17	-140.27	0	-97.25
18	22.68	286.36	75.75
19	-2754.32	-2520.46	-3023.37
20	-95.51	-220.87	-18.92
21	-69.26	-275.54	-3.77
22	0	12.92	0
23	3.81	4.09	-123.82
24	230.02	114.05	198.89
Total cost/ revenue per a day (cent/day)	-7898.42	-8440.13	-8417.82
Deviation (%)	-	+6.42%	+6.17%

noting that negative/ positive amounts show the loss/profit of the VEH in the RT stage. According to obtained results, deploying BESS and EDRP can reduce the loss of VEH in the RT stage since they reduce the need for purchasing power from the RT market in high electricity prices hours (t= 1, 8, 10). Moreover, implementing flexible units can increase the amount of sold power to the market and consequently boost the obtained profit at some hours (t = 2, 11, 24). Based on obtained results, the imbalanced loss of the VEH in the RT stage can be compensated by 6.42% and 6.17% by considering BESS and EDRP, respectively.

2) HEAT ANALYSIS

In this part, the optimal scheduling of generation and consumption units connected to the heat sector of the VEH is analyzed in the RT stage. To this end, the heating power supplies and consumptions are depicted in Fig.14. It should be pointed out that the depicted heat values above/below the horizontal axis represent the heat generation/consumption. Accordingly, VEH participates in the RT heat market as a consumer in hours t =1, 2, and it has played the role of generator in hours t = 4 -24 since it utilizes the full capacity of GB, EHP, and CHP. Generally, TESS units are charged

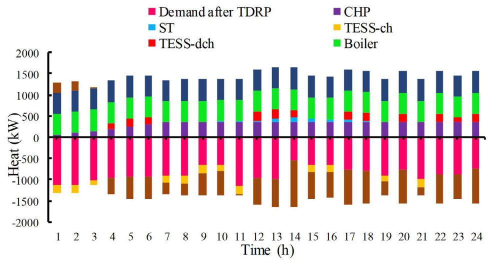

FIGURE 14. Heat Balance.

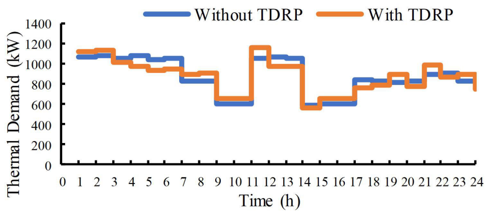

FIGURE 15. The impact of TDRP on the heat load.

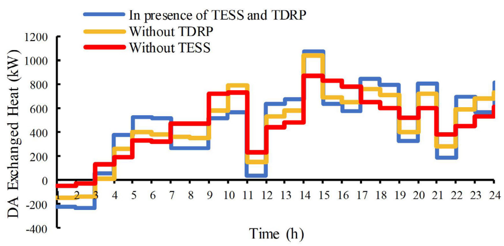

FIGURE 16. The impact of employing TESS and TDRP on the VEH's exchanged heat with DA thermal market.

at off-peak heat price to reduce/increase purchased/sold heat power from/to the heat market. Thus, as evident in this figure, employed TESS is charged at some hours (t = 7-11) at heat off-peak prices. Also, it is discharged in hours (t= 12-14) at heat peak prices. The impact of applying TDRP on the heat demand is depicted in Fig. 15. It is worth mentioning that heat demand is shifted from heat high prices hours to heat low prices hours. Moreover, the impacts of employing TESS and TDRP are investigated in the DA exchanged heat stages in Fig. 16. It should be pointed out that the purchased/sold heat from/to the DA heat market is shown below/above the horizontal axis. As shown in this figure, employing flexible units enables VEH to buy more heat from the market at hours 1 and 2 in off-peak heat prices. Also, it leads to increasing sold heat to the market at some hours (t = 4-7) in high heat prices. In sum, the total revenue of participation of the VEH in the heat market can be increased by 0.62% and 0.25% by employing the TESS and TDRP, respectively.

3) COOLING ANALYSIS

In this section, the optimal scheduling of generating systems and consumption units connected to the cooling sector of the VEH is analyzed in the RT stage in Fig. 17. The values above/below the horizontal axis show the cooling

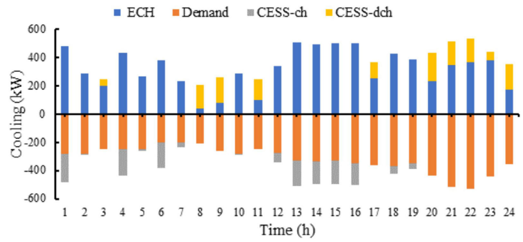

FIGURE 17. Cooling Balance.

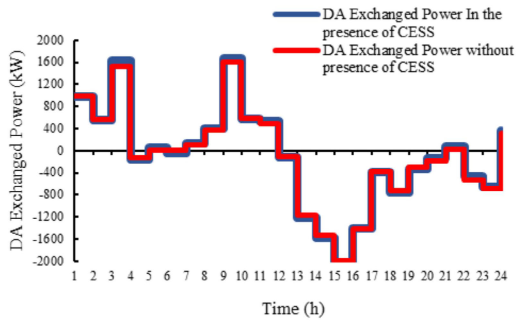

FIGURE 18. The impact of employing CESS on the VEH's exchanged power with DA electricity market.

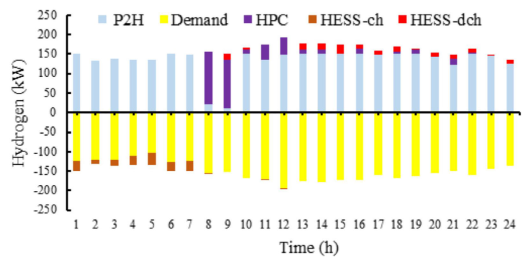

FIGURE 19. Hydrogen Balance.

generation/consumption. ECH is utilized in this system to satisfy cooling demand, which uses electricity and provides cooling. As the performance of ECH is dependent on electricity, at electricity peak prices, the generation of ECH is reduced; meantime, the stored energy in CESS is discharged to satisfy the demand. In other words, cooling storage is charged during off-peak electricity prices hours (t = 12-16) and is discharged during peak electricity prices hours (t = 8, 9).

In this part, the impacts of employing CESS are investigated in DA exchanged power. To this end, in Fig. 18, the amount of purchased/sold power from/to the DA power market is depicted below/above the horizontal axis. As evident in this figure, employing CESS increases sold power to the market at some hours (t = 3, 9). Totally, the revenue of the VEH in the DA and RT power market increases by 0.64% due to the implementation of CESS.

4) HYDROGEN ANALYSIS

In this part, the optimal scheduling of HRS to satisfy the demand for HVs is investigated. The demand can be met

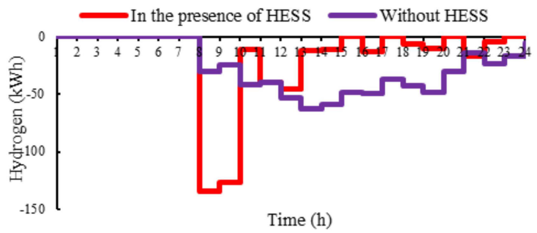

FIGURE 20. The impact of employing HESS on the VEH's exchanged H2 with HPC.

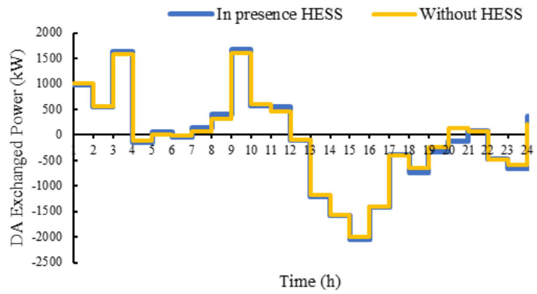

FIGURE 21. The impact of employing HESS on the VEH's exchanged power with DA electricity market .

through P2H production during the scheduling time horizon and also by purchasing H2 from HPC. As shown in Fig. 19, some of the produced H2 by P2H can be stored in HESS (t = 1-8) and then discharged in time intervals corresponding to electricity and H2 high prices (t =13-24). Notably, at time intervals 8 and 9, the production of H2 by P2H is significantly reduced since it is not cost-effective to convert power to hydrogen due to the high price of power. Thus, the operator of VEH prefers to buy H2 from HPC to satisfy its H_2 demand.

Fig. 20 shows the impacts of employing HESS on the purchased H2 from HPC. As shown in this figure, employing HESS enables the operator of the VEH to buy more H2 from HPC during high power prices.

The impacts of employing HESS are investigated in DA exchanged power in Fig. 21. The amount of purchased/sold power from/to the DA power market in/without the presence of HESS is shown below/above the horizontal axis. According to this figure, employing HESS leads to increasing sold power to the market (t = 3, 9) and increasing purchasing power (t=18-20). Totally, employing HESS increases the profit of the VEH by 1.5%.

B. RISK-AVERSE SCHEDULING OF THE VEH BY SOSD-CONSTRAINTS

In this case, the scheduling problem of the VEH is addressed by considering SOSD constraints to provide risk-averse scheduling based on the attitude of the operator toward risk.

1) DETERMINING FEASIBLE REGION OF APPLYING SOSD

By imposing the SOSD constraints on the problem, the amount of profit in the worst scenario can be controlled by predetermined values of the benchmark. Notably, selecting benchmarks while considering the feasibility of the optimal operation problem and fulfilling the VEH operator's risk preference is of great importance. According to [36] solving the risk-neutral and risk-averse problems considering CVaR risk measure with = 1 and = 99% is a practical approach to define the feasible region for selecting benchmarks. Accordingly, the risk-neutral and risk-aversion optimal profit cumulative distribution functions (CDFs) considering each scenario's predetermined probability are obtained. The amount of the worst scenarios in the risk-neutral and risk-averse problem is specified to determine the rectangular region's left and right-hand-side borders. Notably, the range of the vertical axis of the rectangular region is from 0 to 1 according to the predetermined probabilities of each scenario's occurrence rate. The defined rectangular region is called the benchmark's feasible region, which is shown in Fig. 22. Consequently, the risk preference of the manager can be taken into account, while the feasibility of the optimal operation of the problem preserved considering SOSD constraints. In other words, the manager can directly control the amount of profit in the worst scenario in the defined region while being confident that the problem will not be infeasible.

2) IMPOSING SOSD-CONSTRAINTS WITH DIFFERENT SCENARIOS

It is worth noting that the risk preference of the operator of the VEH determines the number of benchmark scenarios, their prefixed values, and probabilities. In Fig. 23, the non-decreasing CDFs of applied benchmarks to the scheduling problem are depicted. Notably, defined benchmark scenarios must be in the feasible region of applying benchmarks to avoid the infeasibility of the scheduling problem with SOSD constraints. Although selecting more benchmark scenarios can provide the operator with more flexibility and better risk management, the computational burden of solving the problem can increase. A one-scenario benchmark can be represented by a vertical line, which limits the worst scenario of the profit distribution not to exceed the predetermined value. Notably, none of the risk-management approaches can directly determine the amount of profit in the worst scenario, which one scenario-SOSD constraint does. In Fig. 24, the one-scenario benchmark and corresponding profit distribution resulting from the imposing one scenario-SOSD constraints to the risk-neutral problem are depicted. By imposing the SOSD constraints with more scenarios to the problem, not only can the amount of the worst profit scenario be controlled, but also the probability of the profit distribution be managed. Fig. 25 and 26 demonstrate the two-scenario and four-scenario benchmark SOSD constraints applied to the risk-neutral scheduling problem and their corresponding profit distributions. Obviously, in these figures, the amount of the profit in worst scenario is controlled in a way that exceeds the prefixed value; also, the probability of the negative tail is limited by predefined probabilities.

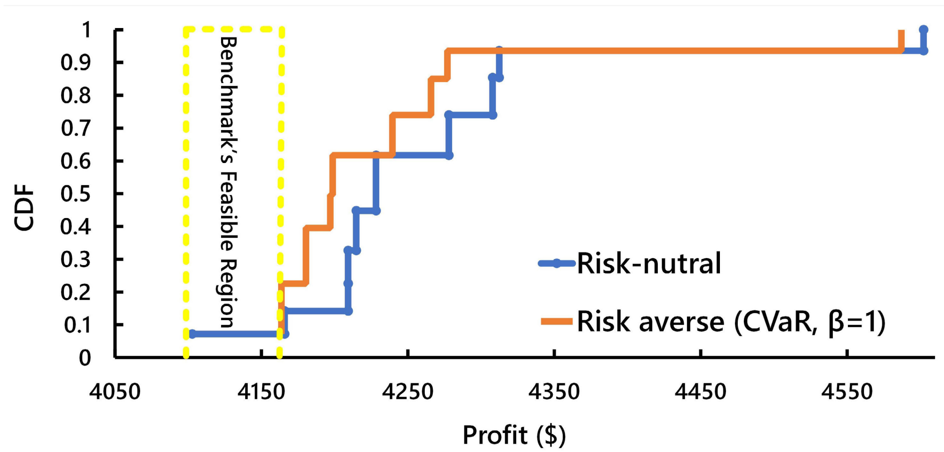

FIGURE 22. The Feasible Region for applying Benchmark.

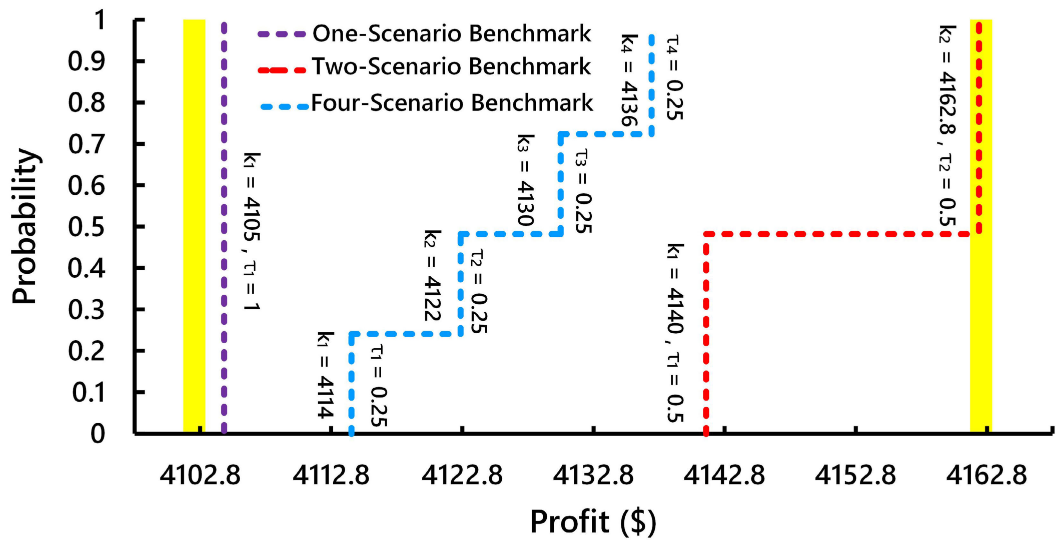

FIGURE 23. CDFs of different Benchmarks with n-scenarios.

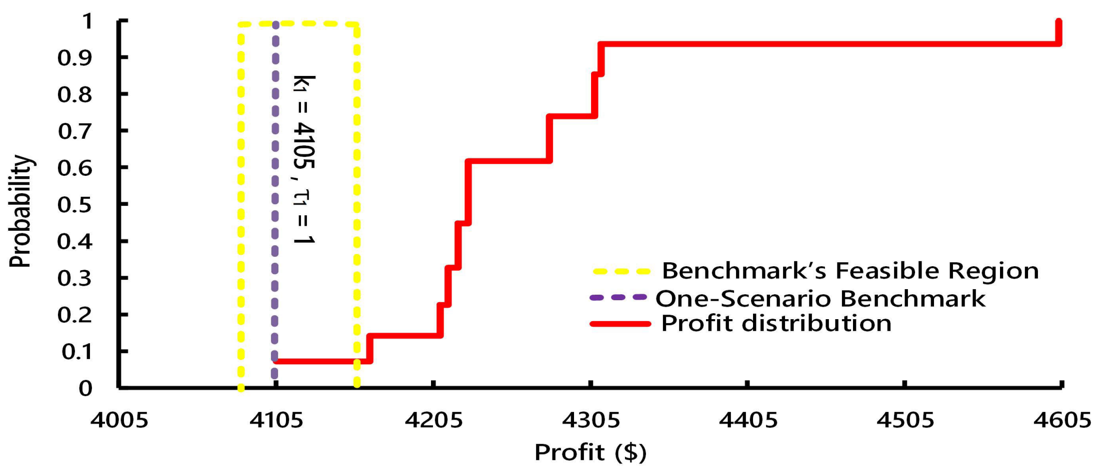

FIGURE 24. One Scenario benchmark and related profit distribution's CDF.

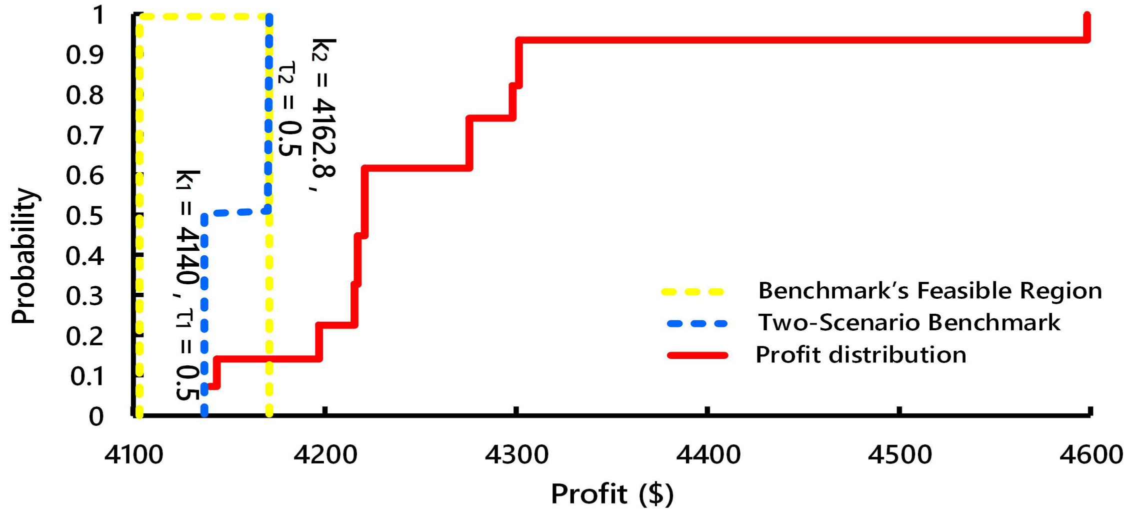

FIGURE 25. Two-scenario benchmark and related profit distribution's CDF.

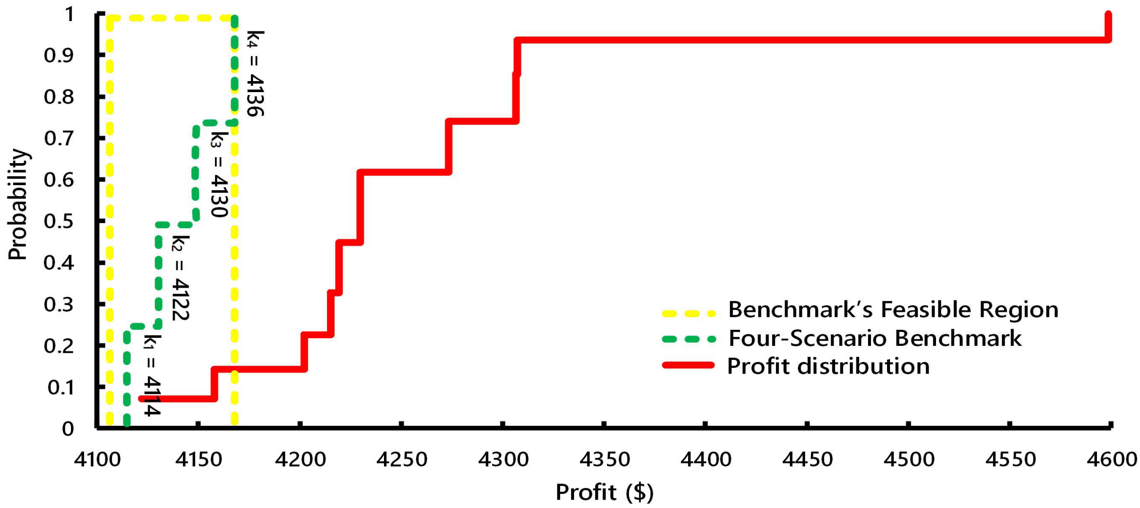

FIGURE 26. Four-scenario benchmark and related profit distribution's CDF.

VII. CONCLUSION

This paper proposed a risk-averse energy management approach for a VEH, including RESs, PtX technologies like EHP and P2H, HVs and IPL, data centers, and energy storage systems to satisfy electricity, heat, cooling, and hydrogen demands. The studied VEH can participate in different energy markets to maximize its benefits. To this, a two-stage stochastic method has been applied to deal with the uncertainties of the problem. Moreover, demand-side energy management is implemented through EDRP and TDRP. The presence of flexible units, including energy storage systems and demand response programs, is evaluated accurately on the expected profit of the studied VEH. According to obtained results, employing a BESS, TESS, CESS, and HESS increases the profit of the VEH by 0.88%, 0.62%, 0.7%, and 1.5%, also implementing EDRP and TDRP can boost the profit of the system by 1.02% and 0.25%, respectively. Moreover, in this paper, SOSD constraints are imposed on the VEH scheduling problem to manage the risk of the optimization problem, including a wide variety of uncertainties. The most controversial point in applying the SOSD constraints is the selection of benchmarks and their corresponding probabilities to avoid the infeasibility of the optimization problem. In this paper, the CVaR risk measure is utilized to determine the feasible region for defining the benchmark distribution function to guarantee the feasibility of the optimization problem. Different case studies with different benchmark distribution functions are conducted to demonstrate the effectiveness of the proposed risk-averse self-scheduling approach of the studied VEH. Results demonstrate that the operator of the VEH can obtain optimal profit distribution based on selected benchmark distribution functions in the feasible region. The superiority of the SOSD risk-management method is that the operator of the system can directly determine the amount of the worst scenario which is impossible in other risk-management methods such as CVaR. In future works, the scheduling problem of the integrated energy system can be addressed while taking into account the market-clearing processes and network constraints.

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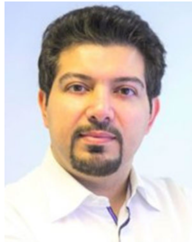

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