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Hybrid IGDT-stochastic self-scheduling of a distributed energy resources aggregator in a multi-energy system

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A R T I C L E I N F O

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A B S T R A C T

The optimal management of distributed energy resources (DERs) and renewable-based generation in multi-energy systems (MESs) is crucial as it is expected that these entities will be the backbone of future energy systems. To optimally manage these numerous and diverse entities, an aggregator is required. This paper proposes the self-scheduling of a DER aggregator through a hybrid Info-gap Decision Theory (IGDT)-stochastic approach in an MES. In this approach, there are several renewable energy resources such as wind and photovoltaic (PV) units as well as multiple DERs, including combined heat and power (CHP) units, and auxiliary boilers (ABs). The approach also considers an EV parking lot and thermal energy storage systems (TESs). Moreover, two demand response (DR) programs from both price-based and incentive-based categories are employed in the microgrid to provide flexibility for the participants. The uncertainty in the generation is addressed through stochastic programming. At the same time, the uncertainty posed by the energy market prices is managed through the application of the IGDT method. A major goal of this model is to choose the risk measure based on the nature and characteristics of the uncertain parameters in the MES. Additionally, the behavior of the risk-averse and risk-seeking decision-makers is also studied. In the first stage, the sole-stochastic results are presented and then, the hybrid stochastic-IGDT results for both risk-averse and risk-seeker decision-makers are discussed. The proposed problem is simulated on the modified IEEE 15-bus system to demonstrate the effectiveness and usefulness of the technique.

1. Introduction

1.1. Background and motivation

The volume of energy generated from distributed energy resources (DERs) is significantly increasing in energy systems. Therefore, it is essential to manage the operation of these devices in the energy systems and a DER aggregator agent can provide this service. This can be done by aggregating the various offers from DERs, including the amount of demand response (DR) and the amount of power through distributed generations, and trading it into the wholesale electricity market to maximize profit [1]. Moreover, it should be considered that the flexibility of a DER aggregator can be enhanced by operating within a multi-energy system (MES) [2]. As before the modernizing the energy system, a microgrid was mainly focused on the electric power sector. However, after the introduction of new models that merge different independent single energy systems into an MES, the microgrid can be utilized for the thermal energy sector as well as the electric energy one [3].

Additionally, as a direct consequence of energy systems restructuring, on one hand, and unprecedented renewable energy utilization on the other, the uncertainties of the energy systems are becoming more challenging. This fact intensifies the difficulty of decision-making in the energy system; therefore, the uncertainty analysis of the system performance is necessary. Moreover, one of the characteristic features of energy system operation and planning is that the decision-making problem is confronted with serious levels of uncertain information in

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Nomenclature

Indexes

s	Scenarios
n	EVs in the microgrid
b, b'	Buses in the network

Parameters

σ	Profit deviation value
ρ_s	Probability of scenarios
$SOC_{n,t,s}^{max}, SOC_{n,t,s}^{min}$	Max/min SOC of EV at time t scenario s
P^{CHPmax}, P^{CHPmin}	Max/min generation of CHP
$\eta_{el}^{CHP}, \eta_{th}^{CHP}$	Electric and thermal efficiency of CHP
$P_{t,s}^{W,max}, P_{t,s}^{PV,max}$	Maximum generation of wind and PV units
$H^{Boilmin}$	Minimum heat of boiler
η_{th}^{Boil}	Thermal efficiency of boiler
$V_{max}, V_{min}, V^{Nom}$	Max/min and nominal voltage
$R_{nn'}, X_{nn'}$	Resistance and reactance of the lines
$\Delta S_{tnn'}$	Upper limit in the discretization of quadratic flow

Variables

$\alpha^{opportunity}$	Optimum opportunity value
α^{robust}	Optimum robustness value
$\mathrm{PR}^{sole\ stochastic}$	Sole stochastic profit of the DER aggregator
$PR_{critical}$	Critical profit of the DER aggregator
PR_{target}	Target profit of the DER aggregator
$P_{t,s}^{W}, P_{t,s}^{PV}$	Power generation of wind and PV units
COP^{HP}	Coefficient of the heat pump
$P_t^{req,HP}$	Power required by the heat pump
P_t^{CHP}	Generation of CHP
H_t^{Boil}	Heat rate of boiler
H_t^{CHP}	Heat rate recovered by the CHP
RU^{CHP}, RD^{CHP}	Ramp-up/ramp-down generation of CHP
$P_{b,t,s}^{L}$	Demand of customers
Pen_t	Penalty in DR programs
A_t	Incentive of DR programs
$P_{b,t,s}^{L,DR}$	Demand by implementing DR
$P_{b,t,s}^{Con}$	Contracted power in DR programs
$P^{Boilmax}$	Maximum generation of boiler
$P_{n,t,s}^{Ch,EV}, P_{n,t,s}^{dis,EV}$	Charging and discharging power of EVs
λ_t^{L}	Electricity price after DR
λ^{g}	Price of natural gas
λ_t^{dis}	Discharging tariff of EVs
λ_t^{EV}	Price of electricity bought by EVs
λ_t^{DA}	Price of electricity from DA market
$P_{t,s}^{Loss}$	Power loss of the system
$V, V2$	Voltage, squared voltage
$I, I2$	Current flow, Squared current flow
$P+, P$	Active power flows in down/upstream sides
$Q+, Q$	Reactive power flows in down/upstream sides
bi_t^{Boil}	Binary variable of boiler
bi_t^{CHP}	Binary variable of CHP

presence of renewable energy resources and wholesale electricity market prices. Therefore, the management of uncertainty through various risk measures such as stochastic programming, information-gap decision theory (IGDT), and robust optimization in the energy system models is crucial [4]. Meanwhile, each uncertain parameter can have its exclusive characteristics which means that employing a single risk-management method for all of these sources of uncertainty, might result in misleading outcomes for a decision-maker. Therefore, to cope with this issue, a hybrid risk management method that manages several uncertain parameters in the MESs based on their characteristics can be proposed.

The DR programs are one of the main solutions to help the energy system to cope with several challenges and issues it has [5]. Meanwhile, the end-user consumers are playing the main role in this area. Hence, it is sufficient to design and offer DR programs in a way to increase the participation rate of the consumers in the DR programs. There are two main classifications for DR programs, price-based DR (PBDR) and incentive-based DR (IBDR) programs [6,7]. Thus, the consumers will find it more conformable to adjust their energy usage pattern based on the various available DR programs rather than a single DR program.

1.2. Literature review

Several studies addressing the management of MESs have been proposed in the literature. For example, the planning and operation of MESs are investigated in Ref. [8] through a two-stage method that determines the optimal type and capacity of electrical and thermal equipment. In this study, electrical, heating, and cooling loads participate in DR programs through an energy pricing strategy. The DER uncertainties in the optimization model are not considered in this work. In Ref. [9], a cooperative framework is proposed to coordinate the operation of a network of MESs that contain electrical and heating loads participating in DR through price-based and incentive-based programs. The behavior of EVs is not simulated in the microgrid and there is no EV parking lot in the energy hub. The authors of [10] developed a modular energy management system for MESs that is generally applicable to various possible electrical, heating, and cooling components.

The management of MESs is subject to several sources of uncertainties such as demand, renewable generation, and electricity market prices. The uncertainty of wind power generation is taken into account in Ref. [11] through a two-stage stochastic formulation that seeks to minimize the operational cost of an MES. In Ref. [12], interval linear programming theory is used to model uncertainties of renewable generation (PV and wind) and demand in the optimal planning of MESs. Wang et al. [13] depict the uncertain behavior of electricity market prices as stochastic scenarios and use robust optimization to describe the uncertainties of renewable generation in a stochastic-robust optimization model for MESs operation. Yet, in Refs. [11–13], the implementation of DR programs is not studied. The study presented in Ref. [14] investigates the use of fuzzy logic to take into account the uncertainties of renewable generation and demand when optimizing the operation of MESs. In Ref. [15], robust optimization for renewable generation uncertainty and a price-based DR program are considered in the day-ahead scheduling of MESs. In another work [16], robust optimization is used for renewable generation and demand uncertainties in an MES that implements DR based on an incentive program. The authors of [17] integrate an incentive-based DR program into a hybrid robust stochastic approach for scheduling MESs. Demand uncertainty is modeled through stochastic scenarios, and wind power uncertainty is taken into account using robust optimization.

The connection of electric vehicles (EVs) increases the complexity of the management of MESs due to the consumption characteristics of the load type. Ata et al. [18] present an optimization framework that schedules the MESs operation considering the impact of EVs, uncertainties of renewable generation through stochastic optimization, and a time-of-use pricing scheme. However, the uncertainty of wholesale market prices, which has a significant impact on the behavior of the decision-maker, is not analyzed. Uncertainties of EVs are considered in Ref. [19] by using a stochastic model predictive control framework that optimizes the MES schedule considering the TOU pricing for electricity. Stochastic optimization is also used in Ref. [20] to model uncertainties of renewable generation and EVs in the MES scheduling problem, considering price-based and incentive-based DR programs. All uncertain parameters in Refs. [19,20] are modeled through a risk-management method disregarding the characteristics and nature of the uncertainties.

A salient characteristic of IGDT is its property of handling the uncertainty problem without depending on the descriptions of the function or fluctuations in the range of uncertain variables. IGDT has been used to model uncertainties in issues related to the power systems, such as the optimal bidding of DER aggregators and optimal bidding of smart microgrids [21,22].

The authors of [23] present a comprehensive approach that models the optimal scheduling of MESs considering uncertainties due to wind energy, demand, EV consumption patterns, and electricity market prices through robust optimization. Further, responsive loads participate in an incentive-based DR program. However, the impact of the favorable variations of the uncertain parameters for a risk-seeking decision-maker is not demonstrated. The authors in Ref. [24] proposed a stochastic-IGDT approach for the management of integrated energy systems. This energy hub consists of a PV unit, a CHP unit, a heat pump (HP) unit, an absorption chiller (AC) unit, a thermal energy storage (TES) system, electric energy storage (EES) system, and an energy demand for heat, cooling, and electricity. The uncertainty of the wholesale market prices is not included in this model. It should be noted that addressing the risk posed by the electricity market prices is crucial for the decision-maker to better inform the self-scheduling strategy. Moreover, the effects of demand-side management methods on the operation of the energy hub and its correlated benefits are neglected.

Wang et al. considered the IGDT method to handle the uncertainty in their proposed MES model [25]. To this end, the uncertainties on renewable energy and load are addressed through a single IGDT method. However, considering the characteristics of the uncertain parameters are ignored in this paper. Moreover, consideration of a single shifting DR program might reduce the tendency of the end-user consumers to participate in the demand-side management process.

The authors in Ref. [26] utilized a hybrid IGDT-robust approach for the self-scheduling of multi-carrier energy systems. The uncertainty posed by wind power generation is handled through the implementation of an IGDT method and the uncertainty of the electricity market price is modeled by the robust optimization approach. The applied IGDT-robust method aims to maximize the horizon of the uncertainty of wind power generation in the worst-case scenarios. Therefore, the IGDT applied to the wind power generation and robust method is managing the day-ahead market prices. The differences between our work relative to this work are mentioned as follows: The generation from various power sources including wind turbines and PV panels and EV charging/discharging patterns is managed through stochastic programming through generation of various scenarios. While the uncertainty of wind power generation in Ref. [26] is handled through robust optimization where only it is managing the worst-case scenarios. Two DR programs from each of the DRP categories are considered in our work to encourage the consumers and end-users to participate more actively in the proposed DR programs. In other words, this provides more flexibility for the consumers to choose the DRP which is more suitable for them. The behavior of both risk-averse and risk-seeking decision-makers is analyzed in our model. While the authors in Ref. [26] only consider the risk-averse behavior of the decision-maker. The study of the risk-seeking behavior of the DER aggregator is beneficial as there is the possibility to have large spikes in the observed electricity market prices which is favorable for the decision-maker and the risk-seeking decision-maker would be interested in having this information beforehand. Thus, risk-seeking decision-makers prefer to pursue the additional benefits of uncertainty therefore can pursue an improved goal, and minimize the negative disturbance of uncertain parameters. Furthermore, the authors in Ref. [27] have implemented a hybrid decentralized stochastic-robust model for the optimal coordination of an EV aggregator and energy hub entities. Stochastic programming is used to model the uncertainties of the EVs patterns, while the uncertainties of the locational marginal prices are modeled via robust optimization to capture the worst-case realization. In this work, the authors considered the EV aggregator and the energy-hub operator as two independent entities while in our model, the DER aggregator is responsible for managing the EVs as well as controlling the generation from the renewable energy resources, designing the demand response programs and offering them to the end-users. While the demand response programs are not taken into account in Ref. [27]. Besides that, merging the role of the EV aggregator, DR aggregator, and the energy-hub operator could lead to making the transaction procedure simpler. Having three different independent entities which in some situations have conflicts of interest might make the optimization procedure more complex.

2. Contributions

As shown in the literature review, the consideration of a suitable risk management method based on the nature and characteristics of the uncertain parameters is found to be an important issue for the DER aggregators in the management and scheduling of MESs. For instance, according to the features of the generation of renewables and DERs, applying the stochastic approach can more accurately address their corresponding uncertainty since the generation of these entities controls the DER aggregator. An aggregator has enough information about the amount of generation from their devices in the MES. However, the DER aggregator does not control the wholesale energy market prices as the aggregator is a price-taker, not a price-maker.

Therefore, with uncertain parameters, the application of the IGDT method is deemed practical. Moreover, the consideration of various DR programs from price-based and incentive-based categories provides flexibility for consumers and encourages them to participate more actively in the DR programs, which is included in this paper. The novel contributions are presented as follows:

- Proposing a hybrid IGDT-stochastic approach for the self-scheduling of a DER aggregator in an MES. Therefore, through the application of this hybrid method, solutions for two different types of DER aggregators (risk-averse and risk-seeker decision-makers) are provided which makes it easier for the decision-makers to choose the model based on their preferences.
- Considering multiple uncertainties posed from both sides of the entity, which are the market side of the aggregator and the consumption side of it, simultaneously. Besides that, the most suitable risk measures for the decision-maker are chosen based on the characteristics of the uncertain parameters, which leads to a more precise decision.

2.1. Paper organization

The organization of the paper is presented as follows. The proposed hybrid IGDT-stochastic model is explained in detail in Section 2. In Section 3, the numerical results are discussed to demonstrate the model's effectiveness. Finally, the conclusion includes the most critical findings, as presented in Section 4.

3. Proposed optimization model

The main objective of the proposed model in the first step, i.e., the sole stochastic programming step, is the maximization of the profit of the DER aggregator through handling the risks associated with the generation of RES and EVs charging/discharging patterns. In the second step, based on the risk strategy, the maximum or minimum deviation of the uncertain parameter from the predetermined values is obtained, while the critical or target profits of the risk-averse or risk-seeker DER aggregator are met and guaranteed. Hence, the proposed MES framework for the DER aggregator includes several sources of DERs such as CHP, boiler units, RESs such as PV and wind units, and thermal energy storage (TES). An EV parking lot is also considered in our model. The inclusion of EVs in the MES could significantly reduce the amount of excess renewable energy produced and also provide more flexibility for the DER aggregator to reduce its management and operational costs, making our model more comprehensive. The schematic of the proposed model is depicted in Fig. 1. As shown in this figure, this model has two inputs (gas and electricity) and two outputs (electrical and thermal loads). As illustrated in Fig. 1, the electricity from the MES is being supplied to two different directions, electrical loads of buildings and the EVs. It should be noted that the DR programs are only implemented on the electrical load of the buildings. The MES under consideration studies several DERs, including CHP units, ABs, and TES systems. Additionally, wind and PV units are included as renewable energy producers. EVs are also included.

As mentioned in the previous section, the two main classifications are price-based DR (PBDR) and incentive-based DR (IBDR) programs. In this paper, DR programs from both categories are considered to provide more flexibility to consumers and encourage them to actively participate in the DR programs. In this case, the flexibility of consumers willing to participate in the DR programs will be increased. A time-of-use (TOU) program is from the PBDR group and the emergency DR programs are from the IBDR group.

To describe the model characterization more in detail, a flowchart of the proposed approach is depicted in Fig. 2. Several sources of uncertainty are managed through a hybrid approach. The behavior of EV owners and the amount of power generated through renewable units, including PV and wind turbines, are modeled with stochastic programming. The uncertainty relating to the wholesale market prices is managed using IGDT. This combination of stochastic and IGDT risk management methods leads to a hybrid IGDT-Stochastic model. In the MES, the DER aggregator has several costs and revenues and this model aims to optimize the self-scheduling model for the aggregator. The proposed model finds the most suitable solution for risk-averse decision-makers. The hybrid IGDT-Stochastic function is modeled in such a way as to protect the aggregator against unfavorable deviations of the uncertain parameter [28], as shown in Fig. 2. Moreover, it can be seen that two sub-stages are considered which form the main hybrid stage. In the first stage, it is assumed that the stochastic risk management method is applied to the associated uncertain parameters such as PV and wind units' generation and the charging pattern of the EVs. Therefore, the uncertainty posed by the electricity market prices is disregarded. In other words, in the first step, it is assumed that there is no uncertainty in the electricity market prices and that the aggregator has perfect foresight about the market prices. Thus, the objective function in this step will become a typical stochastic approach to maximize the profit of the DER aggregator in the MES. Then, in the second sub-section, the IGDT programming is taken into account. The uncertainty of the market prices is measured and addressed in this step. Therefore, the output from the stochastic risk-management method is being used as the input for the IGDT model these two steps together form the main stage, i.e., the hybrid stochastic-IGDT approach. The mathematical model is formulated from two different perspectives to analyze the risk-averse and risk-seeking behaviors of the DER aggregator. Therefore, the optimization strategy is determined at the beginning of the second sub-section. It should be stated that the associated constraints of each step are listed in the flowchart. These constraints will be described in detail in the mathematical formulation subsection.

3.1. Sole stochastic problem formulation

In this step, the stochastic approach is applied to the MES. Hence, to address the uncertainty of the PV, wind units, and EVs, stochastic modeling is well-suited and has been used extensively [20]. Historical data are used to produce the probability distribution functions for each hour to generate the scenarios. The scenario tree method is utilized to generate the scenarios, and the Kantorovich distance method is utilized to reduce the number of scenarios to ease the computation burden. This is done by measuring the distance between several generated scenarios. Then, the scenarios with the minimum Kantorovich distance are found. These scenarios will be omitted and their correlated probability will be added to the reference scenario. Finally, this procedure is repeated until the last batch of scenarios is found [29].

In this step, the objective is to maximize the profit of the DER aggregator considering the uncertainty posed by the PV, wind units, and EVs. It should be noted that the aggregator model contains several terms, which are the primary terms indicating the profit sources and other terms showing the costs of the entity. The energy purchased to satisfy the loads is the main source of income, as well as the DR sold to the customers in peak demand. Finally, the energy sold to the EV owners is the last income term for the aggregator. On the other hand, the main sources that impose costs on the aggregator are the gas and electricity bought from the grid; the DR purchased from the participants in DR programs, the battery degradation cost, and the electricity purchased from the EVs. Thus, the objective function for this stage is written as

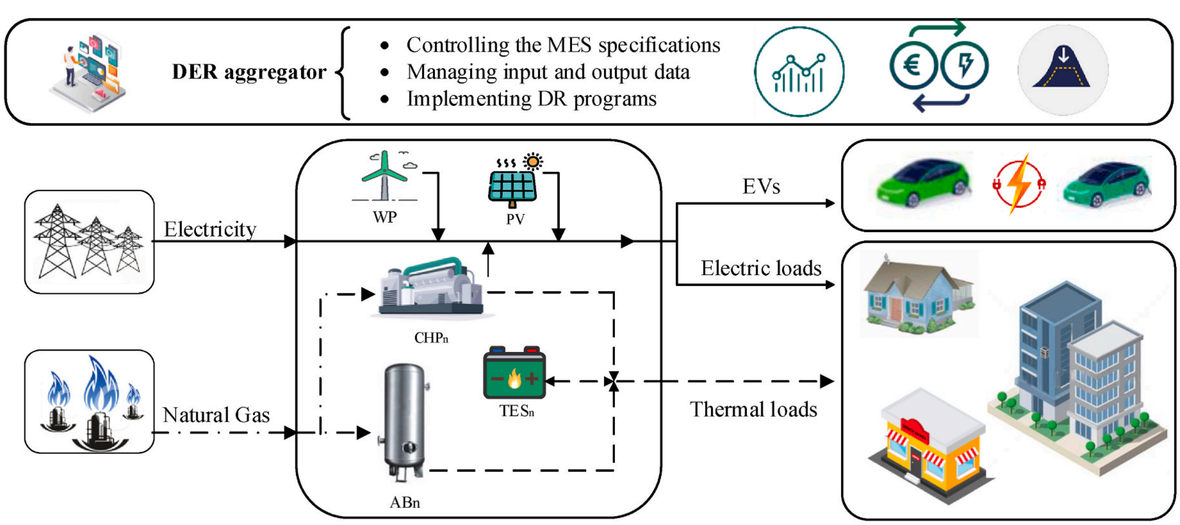

Fig. 1. The schematic of the proposed model.

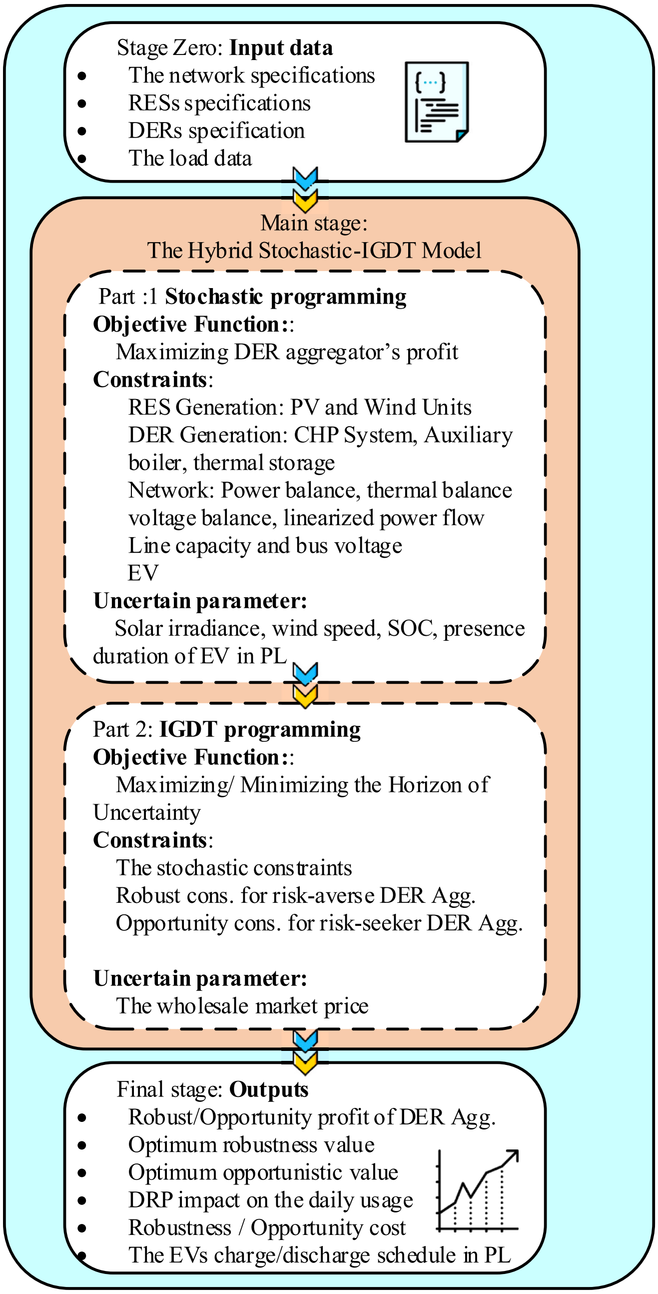

Fig. 2. Flowchart of the proposed hybrid model.

follows:

$$Max\ PR^{sole\ \text{stochastic}} = \sum_{s=1}^{S} \rho_s \left(F_{1,s} + F_{2,s} - F_{3,s} - F_{4,s}\right) \tag{1}$$

where $PR^{sole\ \text{stochastic}}$ is the sole stochastic objective function. The first parameter is the probability of each scenario. $F_{1,s}$ is the aggregator's income from selling electricity to the consumers in the MES. $F_{2,s}$ is the amount of profit obtained through trading with the EVs. $F_{3,s}$ is the cost of purchasing energy from the upstream network. Finally, $F_{4,s}$ is the cost of implementing the DR programs on the proposed MES.

The detailed problem formulation for the first source of income, i.e., $F_{1,s}$ is given as follows:

$$F_{1,s} = \sum_{b=1}^{B} \sum_{t=1}^{T} P_{b,t,s}^{L}\, \lambda_t^{L}\, d_t \tag{2}$$

Thus, in Eq. (2), $P_{b,t,s}^{L}$ indicates the load demand on bus b, time t, and scenario s that is being sold at the electricity price of λ_t^L and d_t is the time interval. The second income source of the DER aggregator is the amount of revenue obtained from selling energy to the EVs minus the cost of buying energy from the EV owners as given in Eq. (3). In this equation, $P_{n,t,s}^{Ch,EV}$ and $P_{n,t,s}^{dis,EV}$ are the charging and discharging values of the EVs where n is the index for the EV, t is the correlated charging time, and s indicting the scenario. The charging and discharging prices of EVs are denoted by λ_t^{Ch} and λ_t^{dis}, respectively. Then, in the last term of this constraint, the degradation cost of the EV battery is calculated, which usually occurs during the discharge. As stated in Ref. [30], the life cycle of EV batteries is usually affected by the depth of discharge. Therefore, to motivate the EV owners to participate in the scheduling plan of the DER aggregator, this cost is reasonable to be covered by the aggregator. Otherwise, the EV owners will not be encouraged to follow the charging and discharging patterns managed by the aggregator. Hence, the aggregator pays the degradation cost on each discharging period based on a specific price denoted by C^d.

$$F_{2,s} = \sum_{n=1}^{N} \sum_{t=1}^{T} \begin{pmatrix} P_{n,t,s}^{Ch,EV} \lambda_t^{Ch} d_t \\ -P_{n,t,s}^{dis,EV} \lambda_t^{dis} d_t - P_{n,t,s}^{dis,EV} C^d d_t \end{pmatrix} \tag{3}$$

Eq. (4) shows the costs of trading energy with the upstream electricity and gas markets. $P_{Sb,t,s}^{DA} \lambda_t^{DA} d_t$ shows the cost of buying electricity, i.e., $P_{Sb,t,s}^{DA}$ from the day-ahead market with a λ_t^{DA} electricity day-ahead market price. The second and third terms are the costs of purchasing gas to feed the CHP units. Thus, P_t^{CHP}/H_t^{CHP} is the amount of power/heat generated through CHP, η_{el}^{CHP} and η_{th}^{CHP} are the electric and thermal efficiency of CHP and LHV_g showing the lower heat value of natural gas. The last term in this constraint is the cost of the auxiliary boiler, where H_t^{Boil} is the heat that is generated by the unit considering the thermal efficiency of the boiler and LHV_g. The upstream gas price is denoted by λ_t^g.

$$F_{3,s} = \sum_{Sb=1}^{Sb} \sum_{t=1}^{T} \left(P_{Sb,t,s}^{DA} \lambda_t^{DA} d_t + \left[\frac{P_t^{CHP}}{\left(\eta_{el}^{CHP} LHV_g\right)} + \frac{H_t^{Boil}}{\left(\eta_{th}^{Boil} LHV_g\right)} \right] \lambda_t^g d_t \right) \tag{4}$$

The cost of implementing the DR programs in the proposed framework is considered in Eq. (5). Two DR programs are assumed for this model, the TOU and the emergency DR programs. These programs are applied to make the proposed framework more comprehensive by providing more flexibility to the consumers to choose the DR method based on their preferences and encouraging the consumers to participate more actively. The TOU program belongs to the price-based DR category, and the emergency DR is categorized as an incentive-based DR program. In the following constraint, A_t is the value of the incentives of the DR program; $P_{b,t,s}^{L}$ indicating the initial demand of the end-user consumer at bus b, time t, and scenario s. Then, $P_{b,t,s}^{L,DR}$ is the amount of demand after the implementation of the DR program from the consumer. The difference between these two values is the amount of DR available for the DER aggregator. However, there is a possibility that the consumers do not participate in the DR program which is deducted from the cost that is imposed on the aggregator which is calculated through the second part of the constraint that is indicated by a negative sign, where $P_{b,t,s}^{Con}$ is showing the contracted power in DR programs.

$$F_{4,s} = \sum_{b=2}^{Nb} \sum_{t=1}^{T} \begin{pmatrix} A_t \left(P_{b,t,s}^{L} - P_{b,t,s}^{L,DR}\right) - \\ Pen_t \left(P_{b,t,s}^{Con} - P_{b,t,s}^{L} + P_{b,t,s}^{L,DR}\right) \end{pmatrix} \tag{5}$$

The related constraints regarding the DR program are given as follows:

$$E = \frac{\lambda_0}{P_0} \cdot \frac{\partial P}{\partial \lambda} \tag{6}$$

$$E_{t,t} = \frac{\lambda_{0,t}}{P_{0,t}} \cdot \frac{P_t - P_{0,t}}{\lambda(t) - \lambda_{0,t}} \leq 0 \tag{7}$$

$$E_{t,t'} = \frac{\lambda_{0,t'}}{P_{0,t}} \cdot \frac{P_t - P_{0,t}}{\lambda_{t'} - \lambda_{0,t'}} \geq 0 \tag{8}$$

$$P^{L,DR}_{b,t,s} = P^{L}_{b,t,s} \left\{ 1 + \sum_{t' \in \mathrm{T}} \frac{\lambda_{t'} - \lambda_{0,t'} + A_{t'} + Pen_{t'}}{\lambda_{0,t'}} E_{t,t'} \right\} \tag{9}$$

The price elasticity is introduced in Eq. (6), which is the reaction of the load change to a change in the price. The self-elasticity and cross-elasticity values are calculated through Eq. (7) and Eq. (8), respectively. The load value after implementing the DR programs is calculated by Eq. (9). $P^{L}_{b,t,s}$ is the initial load without activating the DR programs. The new and initial prices are denoted by λ_t and $\lambda_{0,t}$, respectively. $\mathrm{A_t}$ is the incentive amount of the emergency DR program, $\mathrm{Pen_t}$ is the amount of penalty that must be paid if the DR is not exercised and $\mathrm{E_{t,t}}$ is the elasticity value based on the time of the DR application. This elasticity calculation method is extracted from Ref. [31].

The related constraints of the renewables, DERs, EV and the network and line limitations for the proposed model are presented as follows:

$$P^{W,min}_{t} \leq P^{W}_{t,s} \leq P^{W,max}_{t} \tag{10}$$

$$P^{PV,min}_{t} \leq P^{PV}_{t,s} \leq P^{PV,max}_{t} \tag{11}$$

The constraints (10) and (11) ensure that the renewables in the MES have a minimum and maximum capacity of generation for each time interval and that their generation cannot exceed these values. Then, the following section presents the constraints for each DER. In these constraints, the binary variables are denoted by $bi^{DER\ X}_{t}$ representing whether the devices are active or not.

1) CHP:

The constraints related to the CHP unit are written as follows:

$$bi^{CHP}_{t} P^{CHP,min} \leq P^{CHP}_{t} \leq bi^{CHP}_{t} P^{CHP,max}, \forall t \tag{12}$$

$$RD^{CHP} \leq P^{CHP}_{t} - P^{CHP}_{t-1} \leq RU^{CHP}, \forall t \tag{13}$$

$$H^{CHP}_{t} = P^{CHP}_{t} \frac{\eta^{CHP}_{th}}{\eta^{CHP}_{e}}, \forall t \tag{14}$$

where P^{CHP}_{t} is the total amount of the generated power by the CHP unit in Eq. (12). This value should be within the allowed range as it cannot be lower or higher than the minimum and maximum capacities, respectively. The ramping constraints are presented in Eq. (13). This constraint

$$P^{DA}_{Sb,t,s} + P^{PV}_{b,t,s} + P^{W}_{b,t,s} + P^{CHP}_{b,t,s} + \sum_{n=1} P^{Dis,EV}_{n,t,s} - \sum_{n=1} P^{Ch,EV}_{n,t,s} + \sum_{b' \in B} \left(P^{+}_{t,b,b'} - P^{-}_{t,b,b'} \right) - \sum_{b' \in B} \left[\left(P^{+}_{t,b,b'} - P^{-}_{t,b,b'} \right) + R_{b,b'} I2_{t,b,b'} \right] = P^{L,DR}_{b,t,s}, \ \forall t, \forall b \tag{22}$$

$$Q^{DA}_{Sb,t,s} + Q^{PV}_{b,t,s} + Q^{W}_{b,t,s} + Q^{CHP}_{b,t,s} + \sum_{n=1} Q^{Dis,EV}_{n,t,s} - \sum_{n=1} Q^{Ch,EV}_{n,t,s} + \sum_{b' \in B} \left(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'} \right) - \sum_{b' \in B} \left[\left(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'} \right) + X_{b,b'} I2_{t,b,b'} \right] = Q^{L}_{b,t,s}, \ \forall t, \forall b \tag{23}$$

shows that the amount of increase or decrease in electric power generation of CHP is dependent on various parameters such as its amount of generation in the previous time interval (P^{CHP}_{t-1}), ramp-down value (RD^{CHP}) and ramp-up value (RU^{CHP}). In Eq (14), the heat generated by the CHP unit is calculated, which is dependent on the generated power through the CHP unit, and the thermal and electrical coefficients.

2) Boiler

The constraint related to the boiler is presented as follows:

$$bi^{Boil}_{t} H^{Boil,min} \leq H^{Boil}_{t} \leq bi^{Boil}_{t} P^{Boil,max}, \forall t \tag{15}$$

The heating generation through the boiler is limited through this constraint, where H^{Boil}_{t} is the heating generation value limited by its min/max capacities where they are denoted by $H^{Boil,min}/P^{Boil,max}$, respectively. The binary variable (bi^{Boil}_{t}) indicates whether the boiler is being exercised in time interval t or not.

3) Thermal energy storage

In the proposed MES, TES stores the extra heat that is not required by the consumers. This energy will be supplied to the consumers when there is a demand for heat and the heat generation in that period is not enough.

$$H^{TES}_{t} = H^{TES}_{t-1} \left(1 - \varphi^{TES}\right) + \left(H^{Ch,TES}_{t} - H^{Dis,TES}_{t}\right), \forall t \tag{16}$$

$$H^{TES}_{t} \leq H^{TES}_{max} \tag{17}$$

$$H^{TES}_{t} \geq 0 \tag{18}$$

$$H^{Ch,TES}_{t} \geq 0 \tag{19}$$

$$H^{Dis,TES}_{t} \geq 0 \tag{20}$$

$$H^{Ch,TES}_{t} \leq H^{CHP}_{t} \tag{21}$$

The heat stored in time interval t is dependent on its previous value and the amount of energy added or removed as stated in Eq. (16). In this equation, the losses are denoted by φ^{TES}, which indicates the thermal energy loss for each time interval. The charge and discharge rates of the TES are denoted by $H^{Ch,TES}_{t}$ and $H^{Dis,TES}_{t}$, respectively. The remaining constraints (17)–(21) clarify the capacity limitations of the TES. The TES has a maximum capacity which is given in (17). Moreover, the variables associated with the stored amount of heat, charge, and discharge rates of the TES cannot be negative, as stated in (18) -(20). Finally, the last constraint regarding the TES ensures that the charging rate of the TES must be lower or equal to the heat stored at time interval t.

In this step, the constraints related to the active, reactive, and heating power balancing equations are presented.

$$H^{CHP}_{t} + H^{Boil}_{t} + H^{Dis,TES}_{t} = H^{L}_{t} + H^{Ch,TES}_{t}, \forall t \tag{24}$$

$$V2_{t,b} - 2R_{b,b'}\left(P^{+}_{t,b,b'} - P^{-}_{t,b,b'}\right) - 2X_{b,b'}\left(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'}\right) - \left(R^{2}_{b,b'} + X^{2}_{b,b'}\right)I2_{t,b,b'} - V2_{t,b'} = 0,\ \forall t, \forall b \tag{25}$$

The active power balance is presented in Eq. (22) where the input of the power to the MES should be equal to its output. Thus, the amount of power traded with the wholesale electricity market and generated power from the PV, wind, and CHP units and the charging/discharging values of EVs in the parking lot and active power flows in downstream directions ($P^{+}_{t,b,b'}$) and active power flows in upstream directions ($P^{-}_{t,b,b'}$) should be equal to the demand from the consumers after the implementation of the DR programs. Similarly, the reactive power balance is also considered in constraint (23). Then, Eq. (24) shows the heating power balance. According to the constraint, the heat generated through CHP, boiler, and the discharged rate of TES must be equal to the head demand of the consumers and the charging rate of the TES. Finally, the voltage balance is calculated through Eq. (25). To calculate the active and reactive power balance, two auxiliary constraints should be calculated as shown by Eq. (26) and Eq. (27). The nominal voltage is denoted by V^{Nom} and maximum current flow from bus b to bus b' is denoted by $I^{Max}_{b,b'}$. The linearized power flow calculations for the radial network are considered in equations (28)–(35), where the linearization technique is taken from Ref. [32]. The authors in Ref. [32] validated the accuracy of this linearization technique for optimal power flow through an illustrative example. The correlated constraint for calculating the power factor is given in Eq. (36).

$$P^{+}_{t,b,b'} + P^{-}_{t,b,b'} \le V^{Nom} I^{Max}_{b,b'},\ \forall t, \forall b \tag{26}$$

$$Q^{+}_{t,b,b'} + Q^{-}_{t,b,b'} \le V^{Nom} \times I^{Max}_{b,b'},\ \forall t, \forall b \tag{27}$$

$$V2^{Nom}_{t,b} I2_{t,b,b'} = \sum_{\tau}(2\tau - 1)\Delta S_{t,b,b'}\Delta P_{t,b,b'} + \sum_{\tau}(2\tau - 1)\Delta S_{t,b,b'}\Delta Q_{t,b,b'},\ \forall t, \forall b \tag{28}$$

$$P^{+}_{t,b,b'} + P^{-}_{t,b,b'} = \sum_{\tau}\Delta P_{t,b,b'}(\tau),\ \forall t, \forall b \tag{29}$$

$$Q^{+}_{t,b,b'} + Q^{-}_{t,b,b'} = \sum_{\tau}\Delta Q_{t,b,b'}(\tau),\ \forall t, \forall b \tag{30}$$

$$\Delta P_{t,b,b'}(\tau) \le \Delta S_{t,b,b'}, \Delta Q_{t,b,b'}(\tau) \le \Delta S_{t,b,b'},\ \forall t, \forall b \tag{31}$$

$$I2_{t,b,b'} \le \left(I^{Max}_{b,b'}\right)^{2},\ \forall t, \forall b \tag{32}$$

$$V^{2}_{Min} \le V2 \le V^{2}_{Max},\ \forall t, \forall b \tag{33}$$

$$V2^{Nom}_{t,b} = \left(V^{Nom}\right)^{2},\ \forall t, \forall b \tag{34}$$

$$\Delta S_{t,b,b'} = \frac{V^{Nom} I^{Max}_{b,b'}}{\tau} \forall t, \forall b \tag{35}$$

$$P_{t,b}{}^{\overline{U}}\ tan\left(cos^{-1}(-\theta)\right) \le Q_{t,b}{}^{\overline{U}} \le P_{t,b}{}^{\overline{U}}\ tan\left(cos^{-1}(\theta)\right),\ \forall t, \forall b \tag{36}$$

In addition, it should be noted that each line in the considered MES has limits regarding its thermal energy capacity. Thus, the apparent power in each bus in each scenario is denoted by $S_{b,t,s}$ should be lower or equal to its maximum value denoted by $S^{Max}_{b,t}$ at time interval t, as in Eq. (37). Similar limitations also exist for the voltage in each bus voltage, as stated in Eq. (38). In other words, the voltage level of bus b in scenario s and time t ($V_{b,t,s}$) should be higher or equal to 0.95 and lower or equal to 1.05.

$$S_{b,t,s} \le S^{Max}_{b,t} \tag{37}$$

$$0.95 \le V_{b,t,s} \le 1.05 \tag{38}$$

As stated before, in the proposed framework, it is considered that the microgrid has several EVs and their corresponding effects on the problem formulation should be taken into account. Therefore, the constraints related to the EVs are written as follows:

$$0 \le P^{Ch,EV}_{n,t,s} \le bi^{Ch,EV}_{n,t,s} P^{max}_{n}\ \forall n, \forall t, \forall s \tag{39}$$

$$0 \le P^{Dis,EV}_{n,t,s} \le bi^{Dis,EV}_{n,t,s} P^{max}_{n}\ \forall n, \forall t, \forall s \tag{40}$$

$$0 \le bi^{Ch,EV}_{n,t,s} + bi^{Dis,EV}_{n,t,s} \le 1 \forall n, \forall t, \forall s \tag{41}$$

$$SOC^{EV}_{n,t,s} = SOC^{EV}_{n,t-1,s} + \left(\frac{P^{Ch,EV}_{n,t,s}\eta_{ch} d_t}{E^{CH,Max}}\right) - \left(\frac{P^{Dis,EV}_{n,t,s} d_t}{E^{CH,Max}\eta_{dis}}\right) + \mathrm{SOC}^{\mathrm{EV,Arv}}_{\mathrm{n,t,s}} \tag{42}$$

$$SOC^{min}_{n,t} \le SOC^{EV}_{n,t,s} \le SOC^{max}_{n,t} \forall n, \forall t, \forall s \tag{43}$$

$$SOC^{EV}_{n,t,s} = \mathrm{SOC}^{\mathrm{EV,dep}}_{\mathrm{n,t,s}} \forall n, \forall t, \forall s \tag{44}$$

In our proposed model, the charging and discharging power of each EV is denoted by $P^{Ch,EV}_{n,t,s}$ and $P^{Dis,EV}_{n,t,s}$ in time interval t and scenario s cannot be more than their maximum capacities, as stated in (39) and (40), respectively. Moreover, the binary variables ($bi^{Ch,EV}_{n,t,s}$ and $bi^{Dis,EV}_{n,t,s}$) indicate that EVs cannot be charged or discharged simultaneously, which this limitation is employed through Eq. (41). The state of charge (SOC) for each EV is determined by its SOC in the previous time interval ($SOC^{EV}_{n,t-1,s}$) plus the amount of charging or discharging in the current time interval considering the charging and discharging coefficients, which are denoted by η_{Ch} and η_{Dis}, see Eq. (42). Moreover, $E^{CH,Max}$ is the maximum energy level of the EV battery which is required in the calculation of SOC. It should be noted that the SOC cannot exceed its maximum and minimum values, as seen in Eq. (43). The last equation related to the EV, Eq. (44), shows that when the EV departs from the charging point, the SOC of the EV should reach the value desired by the consumer, denoted by $SOC^{EV,dep}_{n,t,s}$.

3.2. Hybrid IGDT-stochastic optimization framework

In this stage, the uncertainty of the wholesale energy market price is considered by implementing the IGDT approach. In other words, the output of the stochastic programming is now utilized as a baseline to employ the IGDT approach. Therefore, this requires converting the solely stochastic problem formulation into a hybrid IGDT-stochastic problem formulation based on the characteristics of the uncertain parameters and considering the most suitable risk measure. The robust structure of the IGDT approach is applied to manage the proposed model for a risk-averse decision-maker. In contrast, the opportunity structure of the IGDT approach is applied to a risk-seeker decision-maker. Risk seekers prefer to pursue the additional benefits of uncertainty, have the opportunity to pursue an improved result, and minimize the negative disturbance of the uncertain parameters. As we considered the electricity-market prices as the uncertain parameter which is being addressed by IGDT, it should be mentioned that unexpected high price spikes occur in electricity markets, and are favorable price variations for the DER aggregator. A risk-seeker decision-maker desires to benefit from these favorable variations using an opportunity function.

The problem formulation is presented in two different designs, that is, robust and opportunity forms. In the formulation for the risk-averse DER aggregator, the objective is to maximize the horizon of the uncertainty (denoted by α^{robust}) of the energy market prices, while the critical profit of the entity is guaranteed, which is denoted by $PR_{critical}$. The critical profit is defined as the minimum possible amount of profit considering the horizon of uncertainty. Thus, the hybrid IGDT-stochastic model for the risk-averse aggregator is formulated mathematically through Eq. (45) to Eq. (49). The defined robust function requires fulfillment of a set of constraints that can happen in the worst-case scenarios. In other words, the DER aggregator wants to immune its self-scheduling from the scenarios that can prevent the aggregator from achieving lower profits than the critical value.

As stated in (46), the robust profit of the DER aggregator should be higher or equal to the predetermined critical profit denoted ($PR_{critical}$). The critical profit is calculated by a percentage of the result obtained from the stochastic programming ($PR^{sole\ stochastic}$). Therefore, σ is the profit deviation factor. As the profit deviation factor increases, the decision-maker would become more conservative against the unfavorable variations of the wholesale electricity market prices. Hence, σ controls the level of uncertainty which is a value between 0 and 1. $\sigma = 0$ means that the DER aggregator is risk-neutral against the electricity market prices while the uncertainties managed through stochastic programming are applied. In constraint (47), the fractional info-gap uncertainty model is presented [33]. The model is also still governed by Eq. (10) through Eq. (44).

$$\widehat{\alpha}(P, PR_{critical}) = Max\ \alpha^{robust} \tag{45}$$

Subject to:

$$PR_{robust} \geq PR_{critical} = (1-\sigma)PR^{sole\ stochastic} \tag{46}$$

$$\left(1-\alpha^{robust}\right)PR^{sole\ stochastic} \leq PR_{robust} \leq \left(1+\alpha^{robust}\right)PR^{sole\ stochastic} \tag{47}$$

$$Eq.\ (10) - (44) \tag{48}$$

To formulate the problem in a way that the worst-case scenario occurs, the low range of the uncertain parameter, which is the day-ahead electricity market prices, should be chosen. Thus, if $PR_{robust} = (1 - \alpha^{robust})PR^{sole\ stochastic}$, the lowest amount of the profit will be obtained. Therefore, in the above problem formulation, Eq. (48) is replaced by Eq. (49).

$$PR_{robust} = \left(1-\alpha^{robust}\right)PR^{sole\ stochastic} \tag{49}$$

On the other hand, the objective of the risk-seeker DER aggregator is to determine the minimum value for the uncertainty horizon denoted by $\alpha^{opportunity}$ of the energy market prices, which can lead to the achievement of target profit for the entity, denoted by PR_{target}. Therefore, the full hybrid IGDT-stochastic model for the risk-seeker aggregator is formulated mathematically by Eqs. (50) – (53). The objective function is formulated in Eq. (50). The risk-seeker decision-maker desires to analyze the amount of uncertainty horizon if the uncertain parameter deviates favorably using the opportunity form of the IGDT method. As it is common to observe high spikes in the electricity market prices. The opportunity profit, denoted by $PR_{opportunity}$ is profit the DER aggregator will gain if the uncertain parameter deviates favorably. This value should be greater or equal to the target profit denoted by PR_{target}. Target profit is calculated based on the percentage of the result obtained from the stochastic programming. Similar to the robust form, the degree of risk-seeking is chosen by σ as the profit deviation factor. As σ increases, the decision-maker becomes more risk-seeking relative to the wholesale market prices. The constraint (52) indicates that the opportunity profit can be within a range that is dependent on the horizon of the uncertainty ($\alpha^{opportunity}$) and profit of the aggregator gained from the stochastic programming. The model is also still governed by Eq. (10) through Eq. (44).

$$\widehat{\beta}\left(P, PR_{target}\right) = \min\ \alpha^{opportunity} \tag{50}$$

Subject to:

$$PR_{opportunity} \geq PR_{target} = (1+\sigma)PR^{sole\ stochastic} \tag{51}$$

$$\left(1-\alpha^{opportunity}\right)PR^{sole\ stochastic} \leq PR_{opportunity} \leq \left(1+\alpha^{opportunity}\right)PR^{sole\ stochastic} \tag{52}$$

Table 1
Matrix of elasticity.

	Peak	Mid-peak	Off-peak
Peak	−0.3	0.15	0.1
Mid-peak	0.15	−0.3	0.01
Off-peak	0.1	0.01	−0.3

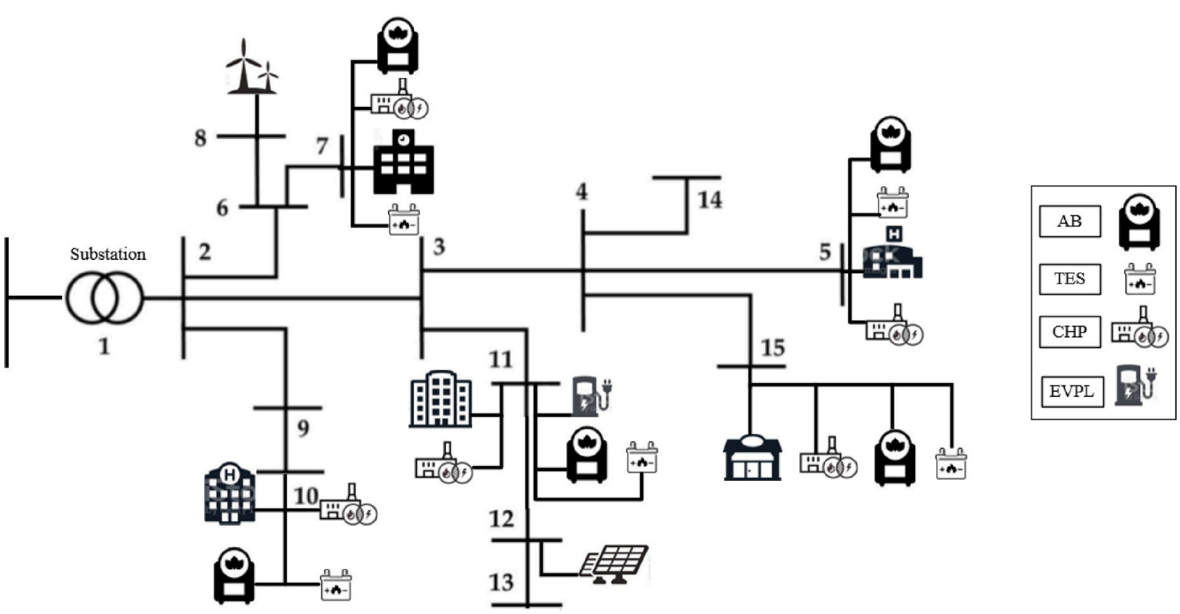

Fig. 3. The structure of the studied modified IEEE 15-bus test system.

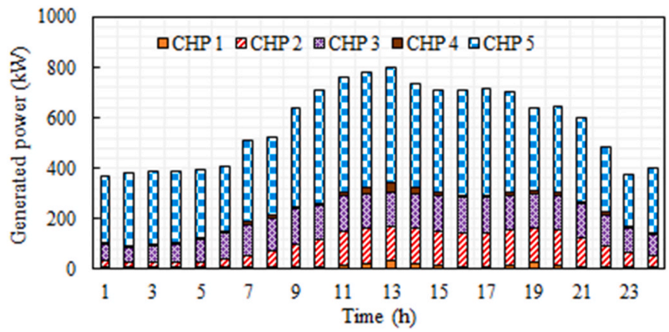

Fig. 4. Power generation of CHP units.

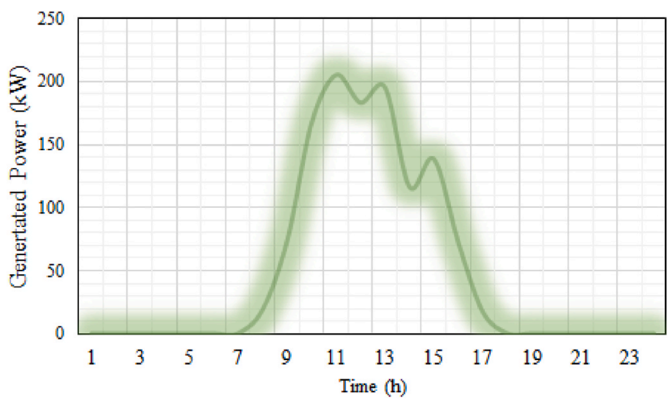

Fig. 5. Power generation of the PV unit.

$$Eq.\ (10)-(44) \tag{53}$$

To formulate the model in the opportunity form, the best-case scenarios should ensure that the profit of the DER aggregator reaches the target profit. This situation happens only if favorable deviations for the uncertain parameter from the baseline values occur. Thus, the highest amount of value for opportunity profit will be obtained if $\mathrm{PR}_{opportunity} = (1 + \alpha^{opportunity})PR^{sole\ \mathrm{stochastic}}$. Therefore, the constraint (52) in the above form of problem formulation is replaced by Eq. (54).

$$\mathrm{PR}_{opportunity} = \left(1+\alpha^{opportunity}\right)PR^{sole\ \mathrm{stochastic}} \tag{54}$$

4. Discussion of results

4.1. Data preparation and assumptions

The proposed hybrid IGDT-stochastic model is formulated as a mixed-integer non-linear programming (MINLP) problem. The problem is modeled in GAMS and two different solvers are utilized: SBB and DICOPT. The model is simulated using a PC with 6 GB RAM and 2.43 GHz CPU speed and The Network-Enabled Optimization System (NEOS) Server [34]. Load data is taken from Ref. [20], where the model is employed on the modified IEEE 15-bus system which is illustrated in Fig. 3. The expected wholesale day-ahead market prices are taken from Ref. [35]. However, MESs were not considered in Ref. [35], while this paper considers a multi-energy framework for the DER aggregator with CHP, boiler units, RESs (namely wind and PV units, installed on bus 12 with nominal power of 200 kW), and TES.

The EV parking lot is allocated to bus 11 in the test system with a capacity of 50 EVs. For the implementation of the DR programs, the time horizon is divided into three time slots, namely peak periods (11:00–15:00 and 19:00–21:59), mid-peak periods (7:00–10:59 and 15:00–18:59), and an off-peak period (22:00–6:59). The elasticity

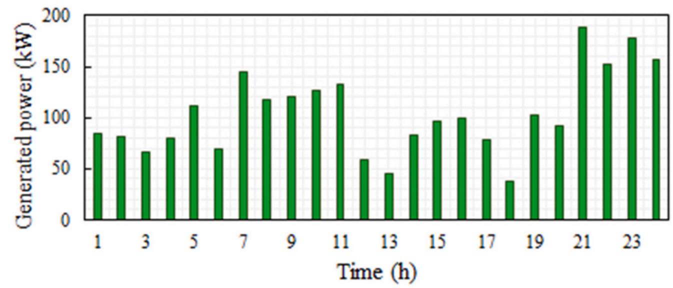

Fig. 6. Power generation of the wind turbines.

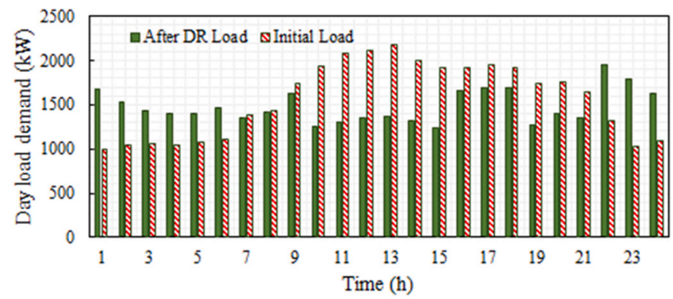

Fig. 7. Daily profile of the consumers before and after DR implementation.

matrix for the DR programs is presented in Table 1. The charge and discharge efficiencies of the EVs are 95% and 90%, respectively. The nominal capacity of the EV battery is equal to 50 kWh with a 10 kW/h SOC. It is assumed that the EV batteries can be charged to a maximum of 85% of the nominal value.

4.2. Sole stochastic optimization stage

In the first stage, it is assumed that there is no uncertainty in the electricity market prices, which are the same as the expected values. Hence, the only uncertainty on the demand side is the generation of the DERs and this is modeled through stochastic programming. Hence, several scenarios are being generated based on historical data. In this case, the value of the objective function, which is the profit of the DER aggregator, is equal to €112,900.

In the MES, there is a set of CHP units used to produce a percentage of power supplied to the consumers. Based on the details of the problem formulation, Fig. 4 illustrates the cumulative value of the power generated from each CHP unit. Due to its characteristics and size, CHP 5 is responsible for the highest generation among the CHP units. The generation of the units is managed by the aggregator. According to this figure and the generation of wind units and PV arrays presented in Fig. 5 and Fig. 6, the CHP units are being used at their maximum capacities when there is low generation from the other DERs. For instance, at 13:00, there is insufficient generation from both PV and wind units. Therefore, the CHPs generate a significant amount of energy to meet the demand and control the fluctuations due to renewables. The generation of renewable energy resources is highly dependent on the weather conditions such as wind speed and solar radiation.

There are hours with low solar irradiation, for example at 14:00 in Fig. 5. Similarly, the wind speed also fluctuates rapidly causing high output in some periods and low output in others, such as at 13:00 in Fig. 6. These fluctuations are controlled and managed by the DER aggregator through other generation units and the implementation of the DR program. A DR program is applied to the proposed model to shift a percentage of the demand from the peak period to the off-peak or mid-peak hours. Fig. 5 Shows the load demand profile in the studied time horizon.

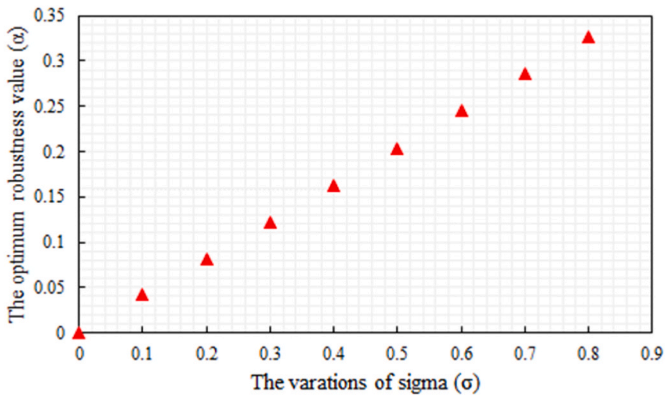

Fig. 8. Optimum robustness values of $\widehat{\alpha}$ for different variations of σ in a risk-averse strategy.

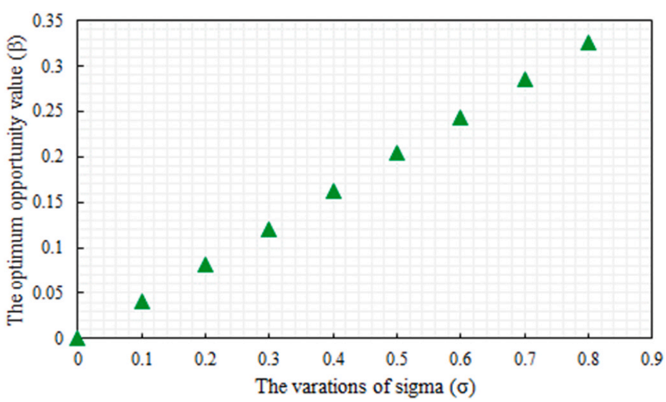

Fig. 9. The optimum robustness value $\widehat{\beta}$ for different variations of σ in a risk-seeking strategy.

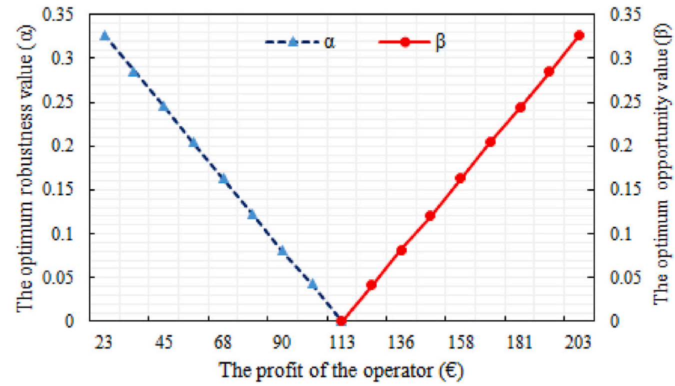

Fig. 10. Optimal $\widehat{\alpha}$ and $\widehat{\beta}$ for different profits of DER aggregators in both risk-averse and risk-seeking strategies.

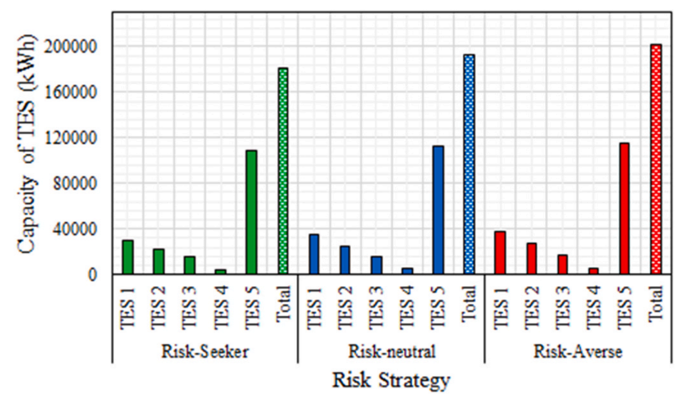

Fig. 11. The optimum stored heat of TESs under various risk strategies.

According to Fig. 7, when there is no DR program, there is a significant difference in consumption. There is low demand during the off-peak period and high demand during the high-peak period. By implementing the DR program, some of the demand is shifted from the peak hours to the off-peak or mid-peak periods. In the early hours of the morning, with a low demand before the DR program, this load is now increased. The DR program increases electricity usage during the off-peak period and decreases consumption during the peak period.

4.3. Hybrid IGDT-stochastic optimization stage

In the next stage, the uncertainty of the electricity market price is considered through IGDT. In this case, the uncertain parameters from both sides are considered The uncertainty around the wholesale market side is managed through the IGDT method, and the uncertainty of renewable energy resources and EV charging/discharging patterns are assessed through stochastic programming. Therefore, the hybrid IGDT-stochastic optimization is implemented in this stage which is mentioned as one of the contributions of our work as considering the different risk measure for multiple sources of uncertainty based on their characteristics. The DER aggregator is assumed to have the forecasted wholesale market prices, i.e., $\{\overline{\lambda}_1, \overline{\lambda}_2, \ldots, \overline{\lambda}_{24}\}$. Then, the hybrid IGDT-Stochastic model is solved for several variations of σ. Therefore, several $PR_{critical}$ values are obtained. As stated in the problem formulation section, the proposed model for both types of decision-makers, risk-averse and risk-taker DER aggregators, is studied. The risk-averse decision-maker aims to guarantee the critical profit even if the worst-case scenario occurs. This type of uncertainty can be studied by implementing the robust function of the IGDT approach. On the other hand, the risk-seeking aggregator accepts the risks when targeting higher profits if a favorable scenario happens. Thus, the behavior of risk-seeking decision-makers is addressed through the opportunistic function of the IGDT approach. Therefore, the effect of considering the uncertain parameters in several risk strategies is depicted in Figs. 8–10.

In Fig. 8, the optimum robustness value for different σ variations is presented. As expected, increasing σ leads to higher amounts of $\widehat{\alpha}$. To explain the behavior of the optimum robustness function value for different variations of σ, an arbitrary value is chosen. Let us assume that, for σ = 0.2, the risk-averse decision-maker wants to be sure that in the worst-case scenario, its critical profit won't be lower than $PR_{critical} = (1-\sigma)PR^{sole\ stochastic} = (1-0.2)\,112,900 =$ €90300. In this case, the optimum robustness value will be equal to 0.08. This means that if the observed market prices deviate by a maximum $\widehat{\alpha} = 0.08$ or 8%, unfavorably, this amount of critical profit is still guaranteed for the aggregator. In Fig. 9, the optimum opportunity function values for different σ variations are shown. By increasing the electricity market prices, higher values for $\widehat{\beta}$ can be found. Similar to the explanation given for the robustness function, an arbitrary σ amount is selected. If σ = 0.2, the target profit of the risk-seeking DER aggregator will be equal to $PR_{target} = (1+\sigma)PR^{sole\ stochastic} = (1+0.2)112,900 =$ €135,500. To reach the € 135,500 aggregator profit, the wholesale market prices should be at least $\widehat{\beta} = 0.08$ or 8% lower than the forecasted values.

In Fig. 10, the optimum robustness function values $(\widehat{\alpha})$ for various profit amounts of the DER aggregator are depicted. On the other side of the graph, the optimum opportunity function value $(\widehat{\beta})$ for different variations of profits is shown. For the risk-averse aggregator, the robust performance of the model is desirable. For instance, as the critical profit decreases, the optimum robustness function increases. This indicates

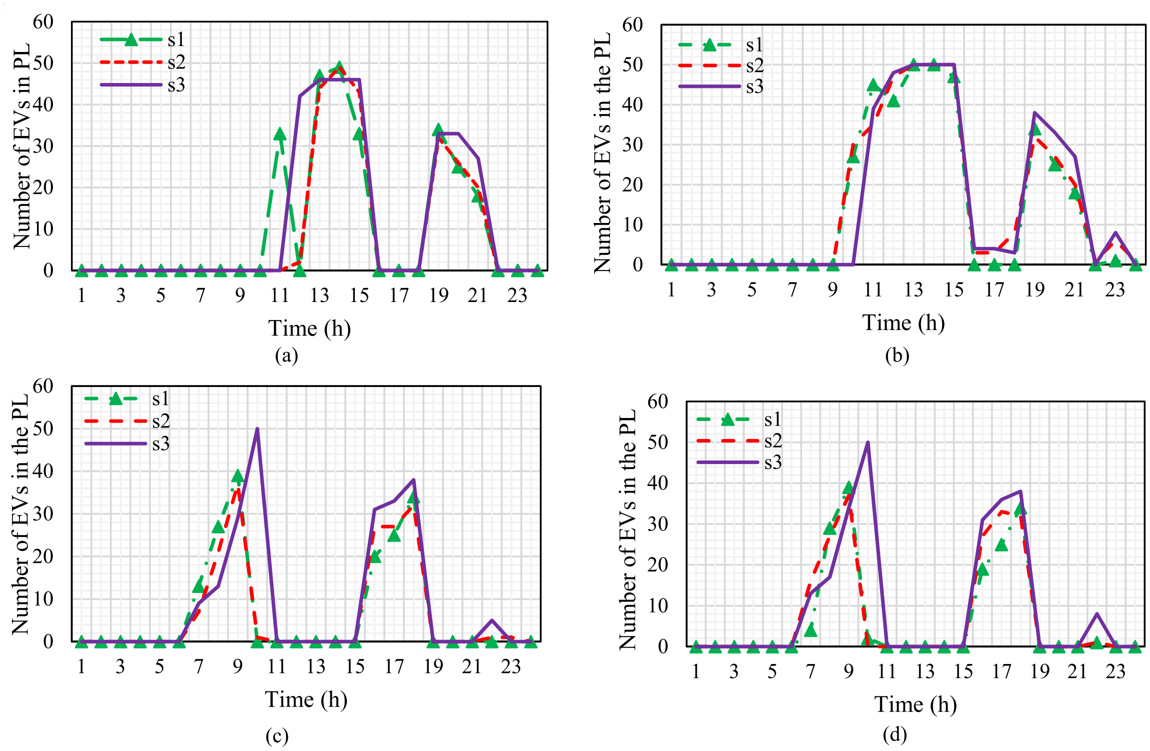

Fig. 12. The behavior of the owners of the EVs in the PL in (a) charging mode in the robust approach; (b) charging mode in the opportunity approach; (c) discharging mode in the robust approach; (d) discharging mode in the opportunity approach.

that higher unfavorable deviations of the uncertain parameter are possible for lower guaranteed critical profits, $\hat{\alpha}$, when the decision-maker chooses the risk-averse strategy. On the other hand, $\hat{\beta}$ is the minimum amount of favorable deviation of the observed values from the forecasted values of the wholesale market prices that ensure the target profit. Another interesting result is that the optimum robustness values and opportunity value for the same variation from the deterministic profit are almost the same and this is illustrated in Fig. 10. Therefore, the optimal values for the two completely different objective functions (risk strategies) result in very similar outcomes.

The optimal values for the stored heat level of the installed TESs are illustrated under various risk strategies in Fig. 11. It can be seen that TES 5 stores a significant level of heat. It should be noted that TES 5 is located on the same bus as the hospital. Therefore, it is essential to ensure that there is enough heat reserve to supply this important consumer. Moreover, it is shown that as the decision-maker chooses to be

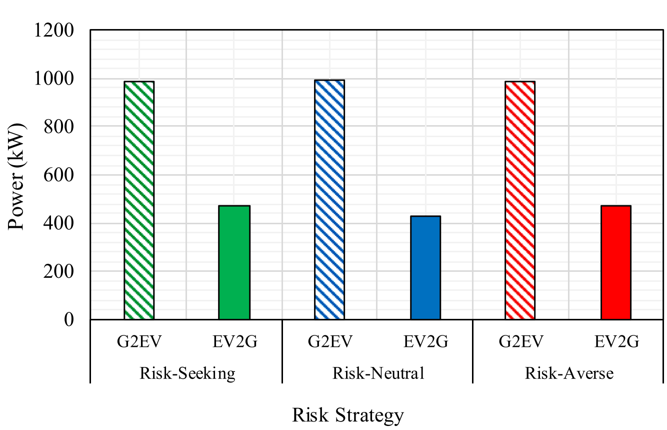

Fig. 13. The optimum values for the grid to vehicle (G2V) and vehicle to grid (V2G) under different risk strategies.

risk-averse, the level of energy in the TES increases. It is due to the characteristics of the risk strategy. The risk-averse DER aggregator prefers to have the highest possible level of energy stored in the TES to make sure it will satisfy the demand of the consumers. In contrast, the risk-seeking aggregator is looking for higher profits which results in lower costs associated with the TES. Therefore, the total energy level of the TES in the risk-seeking strategy would be lower than the other strategies, i.e., risk-neutral and risk-averse.

The behavior of the EVs in the PL in different conditions is shown in Fig. 12. Fig. 12 (a) and (b) present the charging of EVs in the robust and opportunity conditions, respectively. Similarly, sub-figures Fig. 12 (c) and (d) show the discharging of the EVs in the robust and opportunity conditions, respectively. Three scenarios are chosen for each of the robust and opportunity conditions to analyze the impact of the risk attitude of the proposed approach for various scenarios. It can be seen that the number of EVs based on the several scenarios considered the robust and opportunity strategies do not affect the behavior of the EVs in the parking lot significantly. While considering risk management strategies for the decision-maker, being robust or opportunistic does not affect the optimal result of the proposed model. Therefore, in either strategy, there are periods that the parking lot is occupied at its maximum capacity, 50 EVs, regardless of the aggregator's risk attitude.

Table 2
The robustness cost for various robustness function values.

σ	$\hat{\alpha}$	Robustness cost (€)
0	0	0
0.1	0.043	4327.8
0.2	0.0812	6874.4
0.3	0.122	9003.5
0.4	0.163	11476.3
0.5	0.204	13994.2
0.6	0.245	15602.1
0.7	0.286	18109.5
0.8	0.327	20478.1

Table 3
The opportunity cost for various opportunistic function values.

σ	$\widehat{\beta}$	Opportunity cost (€)
0	0	0
0.1	0.041	4571.4
0.2	0.082	7226.9
0.3	0.12	9103.5
0.4	0.163	12051.3
0.5	0.204	15190.3
0.6	0.244	15889.8
0.7	0.285	18933.4
0.8	0.326	22468.1

To go more in detail, the total amount of power that is exchanged between the microgrid and the vehicles is also depicted in Fig. 13. This figure indicates that the total amount of power in whether grid to vehicle (G2V) or vehicle to grid (V2G) are not affected significantly in both risk-seeking and risk-averse strategies. Therefore, this figure validates the results achieved from Fig. 12 Where different risk strategies do not have a serious impact on the operation and scheduling of EVs and the total amount of power exchanged between the EVs and the microgrid is not so sensitive against the risk strategy.

Furthermore, the implementation of any risk management model for addressing the uncertainties will impose some costs on the decision-maker. It will be essential to identify and quantify these costs to determine what level of risk management the decision-makers should enact based on their level of risk-seeking or risk-aversion. Table 2 and Table 3 display the robustness and opportunity costs of the hybrid stochastic-IGDT method for different optimum robustness index values against variations in σ. According to these results, increasing the level of the risk aversion of the aggregator leads to higher robustness or opportunity cost, which is entirely reasonable. The decision-maker is responsible for evaluating the MES and deciding the degree to which the aggregator is risk-averse in the robustness approach and risk-seeking in the opportunity approach.

5. Conclusion

A hybrid IGDT-stochastic approach is proposed for a DER aggregator in an MES microgrid. The uncertainty posed by the generation of renewable resources and DERs is addressed through stochastic programming. As the DER aggregator is the operator of these entities, the level of generation is under the control of the aggregator. However, the energy market prices are not under the control of the aggregator, and additionally, there is a lack of information about the prices. Therefore, the uncertainty posed by market prices is managed through the IGDT method. There are two different structures for IGDT approaches, the robust structure, and the opportunity structure. The robust IGDT function can find the maximum value of the uncertain horizon, which can guarantee the critical profit of the aggregator in the worst case, even if unfavorable cases occur, which is the main aim of risk-averse decision-makers. However, the opportunity function of the IGDT approach can find the minimum value of the uncertain horizon that can lead to higher possible profits if favorable deviations of the uncertain parameter occur, which is the main goal of risk-seeking decision-makers. The results indicate that the aggregator manages the generation of DERs when there is a lack of generation from the installed renewable resources. For instance, in periods with low PV or wind generation, the CHP unit increases its generation to compensate for the shortage. Moreover, the optimum robustness and opportunistic function values for various amounts of profits of the DER aggregator are calculated to provide several risk levels for risk-averse and risk-seeking decision-makers. By increasing the deviation of the risk factor, σ, the obtained values for $\widehat{\alpha}$ and $\widehat{\beta}$ also, increase. Therefore, as $\widehat{\beta}$ arises, the aggregator becomes more risk-seeking. Similarly, as $\widehat{\alpha}$ arises, the aggregator becomes more risk-averse. Moreover, the imposed cost to the aggregator due to choosing the risk measure and its corresponding level is a crucial factor that should not be neglected. In terms of future work, different energy market structures could be explored to determine the optimal behavior of the DER aggregator.

Credit author statement

Morteza Vahid-Ghavidel: Investigation, Methodology, Data curation, Writing – original draft. Miadreza Shafie-khah: Visualization, Conceptualization, Validation. Mohammad Sadegh Javadi: Formal analysis, Methodology. Sérgio F. Santos: Formal analysis, Methodology. Matthew Gough: Writing – review & editing. Darwin A. Quijano: Validation. Joao P.S. Catalão: Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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