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Short-Term Operation of Microgrids with Thermal and Electrical Loads under Different Uncertainties using Information Gap Decision Theory

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Abstract

The utilization of an Energy Management System (EMS) for the optimum scheduling of generation units, as well as demand side resources is essential due to the high penetration of Distributed Energy Resources (DERs) in microgrids (MGs), to achieve the desired objectives. As a result of the restructuring of the power systems and increasing the electricity prices during some periods in a day, demand side programs have been highly valuable by electricity customers. In this paper, a Demand Response (DR) model has been proposed to present the behavior of responsive controllable loads in response to the DR calls. Moreover, optimal scheduling of energy resources is developed for a typical MG by considering the presence of both electrical and thermal demands. Combined Heat and Power (CHP) units, boilers, wind turbines, storage devices, demand response resources (DRRs), as well as the power exchange possibility with the upstream wholesale market are the energy resources that have been considered as the portfolio of the decision maker. Furthermore, the uncertainty resources of the wind speeds and electrical load are handled by the Information Gap Decision Theory (IGDT) method. The performance of the proposed framework is comprehensively analyzed on the IEEE 33-bus test system. The advantage of the proposed methodology under the uncertainty conditions is analyzed by the Monte-Carlo simulation method when the different realization of the wind power and electrical load are considered.

Keywords: distributed energy resources; demand response; microgrid; combined heat and power; uncertainty.

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Nomenclatures

Indices and sets

i, i': Indices for network buses

Ω_l^i : set of buses connected to bus *i*;

Ω_l : set of lines;

cl: index of the controllable loads of the MG (which have the performance period);

Parameters

$x_{i,i'}$: Reactance of the line between buses *i* and *i';*

$L_{i,t}^E$: Electrical load of bus *i* at hour *t* [kWh];

$H_{i,t}^D$: Thermal demand at hour *t* [kWh];

TL_{max} : Maximum exchanged power between MG and upstream grid [kW];

$MainTD_i$: Length of the performance period of controllable load in bus *i*;

t_l , t_e : Start/end-times of the performance period of the controllable loads;

$LoatTD_{i,t}$: Load level of controllable loads [kWh];

UR_i^{CHP} : Ramping up limit of the CHP unit;

DR_i^{CHP} : Ramping down limit of the CHP unit;

$P0_i^{CHP}$: Initial generating power of the CHP unit.

$\alpha_{CHP}^{th}, \beta_{CHP}^{th}, \gamma_{CHP}^{th}$: Coefficients of the permissible thermal zone constraints of CHP;

P_{CHP}^{min} / P_{CHP}^{max} : maximum and minimum range of the power generated by the CHP unit [kW];

H_B^{min}, H_B^{max} : maximum and minimum range of the thermal power generated by the ancillary boiler [kW];

$\overline{P}_{i,t}^W$: Forecasted power generation of wind turbine *i* at hour *t*;

Variables

F_1: Objective function [$];

$Cost$: Total operation cost of the MG [$];

$Revenue$: Income from selling the electricity of the MG to the upstream grid [$];

$Cost_t^{CHP}$: Total operation cost of the CHP units at hour t, including the thermal and electrical operation costs [$];

$Cost_t^{boi}$: Total operation cost of the boilers at hour t [$];

$Cost_t^{S}$: Total operation cost of the storages at hour t [$];

$Cost_t^{Wind}$: Total operation cost of the wind turbines at hour t [$];

$Cost_t^{buy}$: Total electricity purchase cost from the wholesale electricity market [$];

$P_{i,t}^{CHP}$: Generating electric power of the CHP unit of bus i at hour t [kW];

$H_{i,t}^{CHP}$: Generating thermal power of the CHP unit of bus i at hour t [kW];

$gas_{i,t}^{CHP}$: The volume of gas consumption by CHP unit of bus i at hour t [m^3];

π^{gas} : Gas price ($\$/m^3$);

$H_{i,t}^{boi}$: Thermal power generation of the ancillary boiler in bus i at hour t [kW];

$PD_{i,t}^{s}$: Discharging power of the storage unit of bus i at hour t [kW];

$PC_{i,t}^{s}$: Charging power of the storage units at hour t [kW];

$CD_{i,t}^{s}$: Discharging cost of the storage units at hour t [$/kW];

$P_{i,t}^{W}$: Power generation of the wind turbine at hour t [kW];

c_i^{W} : Cost of electric power generation of the wind turbine [$/kW];

$ep_{buy(t)}$: Cost of the power purchased from the upstream grid at hour t [$/kW];

P_t^{buy} : Power purchased from the upstream grid at hour t [kW];

$ep_{sell(t)}$: Cost of the power sold to the upstream grid at hour t [$/kW];

P_t^{sell} : Power sold to the upstream grid at hour t [kW];

$PL_{i,t}^{E}$: Actual hourly electrical load at bus i [kW];

$PL_{i,t}^{cl}$: Actual electrical load of the controllable loads of bus i at hour t [kW];

$IP_{G(t)}$ / $IS_{G(t)}$: Binary variables denoting the purchasing or selling power to the upstream grid at hour t, respectively;

$XIT_{i,t}$: A binary variable to show the performance of controllable load of bus i at hour t (0: if the load is on; 1: otherwise);

$\alpha_{i,t}^{CHP} / \beta_{i,t}^{CHP}$: The binary variables that denote a unit is going to be turned on/off at the hour t;

$I_{i,t}^{CHP}$: A binary variable representing the on/off status of the CHP unit at the time t (if the unit is on, it is 1; otherwise it is 0).

Abbreviations

MG	Microgrid
IGDT	Information gap decision theory
DER	Distributed energy resources
DSO	Distribution system operator
CHP	Combined heat and power
DG	Distributed generation
DOE	Department of energy
DR	Demand response
GA	Genetic algorithm
PSO	Particle swarm optimization
RER	Renewable energy resources
VPP	Virtual power plant
DRRs	Demand response resources

1. Introduction

The self-healing capability is one of the important goals of a power system. The division of the power systems into several sub-systems (called MGs), is one of the solutions to achieve this objective. MGs are a set of DERs and electrical loads of the distribution systems that could be operated in both the grid-connected or islanded modes. From the viewpoint of the Distribution System Operator (DSO), MGs could enhance the reliability level of the system. Moreover, from the customers' viewpoint, they can provide the improvement of reliability level, voltage profile, and power quality with the minimum electricity curtailments [1].

Various DERs (such as CHPs) are utilized in the MGs. In the CHP-based MGs, the obtained heat from the electricity generation process will be used to supply the thermal demands. In addition to the distributed generation (DG) units, DR programs could be considered as distributed resources. Department of Energy (DOE) defined the DR programs as "a tariff or program established to motivate electrical use by end-use customers in response to changes in the price of electricity over time or to give incentive payments designed to induce lower electricity use at a time of high market price or when grid reliability is jeopardized" [2, 3].

Because of the high benefit potential of DR, these programs have been focused on several studies in recent years [4,5]. Amini et al. [6] provided a survey on DR programs and investigated the importance of these resources in future power networks. Reference [7] described the importance and challenges of DR programs, as well as their future trends. A review is provided in [8] about the DR potentials and benefits in smart grids. In the future power systems, electricity customers have an essential role through the DR contracts, where they are motivated to modify their consumption patterns [9, 10]. On the other hand, consumers have high impacts on the conventional definitions of the power system. These aspects are studied in [11] and [12]. Where they present some vulnerability indices for the consumers and propose a new viewpoint for the system planning in the short-term and long-term horizons. Since the congestion problem in the MGs is not as restricted as the traditional power systems (generally the load points are close to the generation units in the MGs), the commitment of the units in the MGs are easier than the commitment of them in the traditional power systems [13-15].

The MGs can be operated in the islanded or connected mode. The optimal scheduling of generation units is an essential task that should be handled by the system operators. Since the DERs, such as wind and solar units have an important role to satisfy the MG's demand, the optimal scheduling of these resources is vital to efficiently use the potential of these resources. Therefore, different methods such as linear programming [16, 17], and neural networks [18] have been introduced to minimize the operational costs of the MGs. Moreover, the utilization of meta-heuristic algorithms has been proposed by many studies. References [19-21] employed the Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to optimally schedule the generation of MGs' units. In addition to the single-objective models, the multi-objective models have been focused in many studies. In [22], the multi-agent concept is used for the scheduling of DERs. In this paper, the GA and Lagrangian relaxation methods have been employed for the scheduling of MGs. The day-ahead optimal operation of the CHP units by considering the ancillary service constraints is studied in [23]. The proposed model of this paper is a mix-integer linear programming problem that will obtain the best strategy for the power exchange. The aim of this paper is the optimal operation of the units and provide ancillary service contracts to maximize the benefit. Reference [24] introduced a method for minimizing the operation cost of MG using the fuzzy approach to control the storage systems. The Benders decomposition is employed in [25] in order to determine the economic dispatch of a combined heat and power system. In [26], the acceleration coefficients of the PSO method are investigated for the electrical and thermal economic dispatch. Karimi et. al. [27], divided the MG loads into flexible and inflexible loads and developed an approach for the energy management of an MG. A survey is provided in [28] on the fundamentals of the hybrid AC/DC MGs. In this paper, mathematical models of the problem are presented and the generations of different renewable energy resources (RERs) are studied.

A novel optimal operation of the CHP-based MGs is studied in [29] by considering the presence of energy storage devices, three types of thermal generation units and DR programs. Reference [30] investigated the generation scheduling of CHP units and storages, by using a linear model. The responsive loads are not modelled in this paper. Liang et al. [31] reviewed the stochastic modelling, as well as the optimization methods of the MG. Nosratabadi et al. [32], investigated different aspects of the MGs and VPP frameworks, such as modelling, optimization, objective functions, constraints, uncertainties, DR, and multi-objective problems.

The presence of uncertain parameters is one of the main challenges for the planning and operation of MGs. Power generation of renewable energy resources (RER), market prices and load levels are the main resources of uncertainties. The uncertainty modeling approaches have been studied in many researches. Different techniques have been used to model the uncertainties, e.g. stochastic programming [33,34], robust optimization [35-38], and chance-constrained [39-41] methods. The goal of these approaches is to determine the robust solutions that are able to overcome the uncertain nature of the problems. Jirdehi et al [42] have considered the uncertain nature of wind speed, solar radiation, and loads in a multi-objective MG scheduling in which the augmented Epsilon-constraint technique has been employed to solve the problem. In [43], the uncertainty of load, price, and RERs' generation have been considered by using the normal distribution functions. Hussain et al [44] employed a robust optimization method to model the market prices, RERs' generations and load levels. Affine arithmetic (AA) is utilized in [45] to model the interval uncertainties and sensitivities in nodal power injections. Pourghasem et al. [46] presented a stochastic model for optimal management of MGs in which load levels and wind generations are considered in the scenario generation process using a roulette wheel mechanism. A robust multi-objective optimization approach is also used in [47] in order to model the uncertainties caused by intermittent RERs and load levels. [48] represents a system operation problem, in which the wind power uncertainty is modeled using IGDT. However, the other impressive uncertainties are neglected. Uncertainties such as actual load. In [49], short-term scheduling of the bulk power system is performed using the IGDT method. It considers the wind power generation and DR programs as the uncertain parameters. However, its' mathematical formulations, conclusions, and achievements are not fully usable for a MG with different storage units, CHPs, boilers, responsive loads and thermal demands.

The main aim of the paper is to develop an optimization model for the MG scheduling that includes the uncertain parameters. This optimization model is able to schedule both the electrical and thermal power generation resources to supply the load. Also, it takes a distinguished approach for the decision-making under the uncertainty, in which the uncertainties can be undesired or favorable.

In fact, the MG's operator firstly determines a target for the cost or profit; Then, the optimization model calculates the maximum tolerable (minimum needed) amount of the undesired (desired) uncertainties to achieve the predefined targets. As well as, it proposes an approach to combine different uncertainties in a simple manner that results in a single-stage optimization model.

Depend on the optimization strategy, the proposed model provides the optimal scheduling of the MG to supply the thermal and electrical load. It includes different energy resources such as CHP, boiler, wind turbine, energy storage, DR and energy exchange with the main grid. In addition, it considers the power flow equations of the electrical network.

Briefly, the main contributions and novelties of the paper are as follows:

- A comprehensive operation framework is proposed for the DSO by considering the thermal and electrical requirements of a MG;
- A novel linear formulation of DR is presented to model the transferable responsive loads;
- Two different uncertain parameters are simultaneously considered in an IGDT-based optimization model;
- In addition to the immunity against the undesired uncertainties, the proposed scheduling method empowers the MG to make a profit in case of some of the favorable uncertainties.
- A single level structure is developed to formulate the IGDT-based optimization. Its performance is tested by the Monte-Carlo simulation method;
- A proper mixed integer linear model is developed for the optimal scheduling of a MG by considering the power exchange possibility with the upstream grid.
- The sensitivity of the system's cost or profit to the different uncertainty resources is determined using the indices of the IGDT.

The rest of the paper is organized as the following. Section 2 represents IGDT and its uncertainty set modelling. Section 3 represents the mathematical formulation of the MG operation problem. Mathematical modelling of CHP, boilers and DR are elaborated in this section. Section 4 is dedicated to the numerical simulations, and section 5 concludes the paper.

2. Uncertainty modeling using IGDT

MG scheduler generally tries to minimize its' operation costs or maximize its profit. Decision making under uncertainty is a challenging process that introduces risk measures and different strategies for decision making.

There are different methods for uncertainty modeling. In some methods, probability distribution functions have a key role. For example, in stochastic programming, the expected value of the cost or profit is minimized in the objective function. Another method is related to robust optimization, which needs the probability distribution function for identifying the uncertainty set. IGDT is a decision-making method that has no need for the exact uncertainty set. On the other hand, it is capable of modeling the favorable behavior of the uncertain parameters. The different mathematical formulations of the IGDT are introduced in [50]. By considering Λ and ξ respectively as the uncertain parameter and the radius of the uncertainty, this paper assumes such an uncertainty set for IGDT formulation. $\bar{\Lambda}$ is the expected value of Λ.

$$U(\xi,\Lambda)=\left\{\Lambda:\left|\Lambda-\bar{\Lambda}\right|\leq\xi\left|\bar{\Lambda}\right|\right\} \tag{1}$$

There are two main strategies in the IGDT: robustness strategy and opportunity strategy, which will be presented in the following section.

3. The mathematical formulation for short-term MG scheduling

MG contains a set of distributed generation units. As pre-mentioned, in this paper, CHP units, boilers, wind turbines, storage devices, as well as demand response resources (DRRs), are available in the MG. MG's scheduler is a profit maximizer which considers different costs and revenues. At the following subsections, the objective function and mathematical model of the resources are presented.

3.1 Objective function

From DSO's point of view, the problem is minimizing the total operation cost, using an optimal strategy for the operation of CHP units, boilers, wind turbines, storages, and DR resources, as well as the power exchange with the upstream grid. The objective function is formulated by (2)-(11). The operation costs of CHP and boiler are determined by the gas price and their energy efficiency ((4)-(7)).

Equations (8) and (9) are the operation costs of the storages and wind turbines. Energy exchange with the MG leads to costs and revenues which respectively are indicated in (10) and (11).

$$F=\ Max\ \ \{Revenue-Cost\} \tag{2}$$

$$Cost=\sum_{t=1}^{T}\left(Cost_t^{CHP}+Cost_t^{boi}+Cost_t^{S}+Cost_t^{Wind}+Cost_t^{Buy}\right) \tag{3}$$

$$cost_t^{CHP}=\sum_i gas_{i,t}^{CHP}\pi^{gas} \tag{4}$$

$$gas_{i,t}^{CHP} = \sigma^{MWh/m3} \frac{\left(P_{i,t}^{CHP} + H_{i,t}^{CHP}\right)}{\eta_i^{CHP}} \quad (5)$$

$$cost_t^{boi} = \sum_i gas_{i,t}^{boi} \pi^{gas} \quad (6)$$

$$gas_{i,t}^{boi} = \sigma^{MWh/m3} \frac{H_{i,t}^{boi}}{\eta_i^{boi}} \quad (7)$$

$$Cost_t^S = \sum_i CD_i PD_{i,t}^s \quad (8)$$

$$Cost_t^{Wind} = P_t^W c^W \quad (9)$$

$$Cost_t^{buy} = ep_t^{buy} P_t^{buy} \quad (10)$$

$$Revenue = \sum_{t=1}^{T} ep_t^{sell} P_t^{sell} \quad (11)$$

3.2 System constraints

3.2.1 DC power flow

$$P_{i,t}^{inj} = P_{i,t}^{CHP} + PD_{i,t}^s - PC_{i,t}^s + P_{i,t}^W + P_{i,t}^{buy} - P_{i,t}^{sell} - PL_{i,t}^E - PL_{i,t}^{cl} \qquad \forall\ t,i \quad (12)$$

$$P_{i,t}^{inj} = \sum_{i' \in \Omega_l^i} F_{i,i',t} \qquad \forall\ t,i \quad (13)$$

$$F_{i,i',t} = \frac{\theta_{i,t} - \theta_{i',t}}{x_{i,i'}} \qquad \forall ii' \in \Omega_l \quad (14)$$

$$-F_{i,i'}^{max} \le F_{i,i',t} \le F_{i,i'}^{max} \quad (15)$$

3.2.2 Thermal load balance

$$H_{i,t}^{CHP} + H_{i,t}^{boi} = H_{i,t}^{D} \qquad \forall\ \ i,t \quad (16)$$

3.2.3 Constraints of the power exchange with upstream grid

$$P_{i,t}^{sell} \le TL_{max} IP_{i,t} \quad \forall\ t \quad (17)$$

$$P_{i,t}^{buy} \le TL_{max} IS_{G(t)} \quad \forall\ t \quad (18)$$

$$IP_{G(t)} + IS_{G(t)} \le 1 \quad \forall\ t \quad (19)$$

3.3 DR modelling

A part of the load of the MG may be responsive that could be controllable in the specified time periods. This time interval is called the performance period of the load. The response time of each controllable load should be within the start and end times of the performance period of the load.

Each load should be on once in a day. The determination of the performance period of each load depends on the various conditions that will be discussed at the following of the paper. Equation (20) specifies the effect of controllable loads on the total load level.

$$PL_{i,t}^{cl} = LoatTD_{i,t}\left(1 - XIT_{i,t}\right) \quad \forall\ t \tag{20}$$

The usage time of the equipment within the performance period is shown by (21).

$$\sum_{t=t_e}^{t_l}\left(1 - XIT_{i,t}\right) = MainTD_i \tag{21}$$

Constraints (22)-(24) express the time continuity of the performance of the controllable loads.

$$XIT_{(l,t)} = 1 \qquad \forall\ t > t_l \quad or \quad t < t_e \tag{22}$$

$$U_{i,t} - V_{i,t} = XIT_{i,t-1} - XIT_{i,t} \qquad \forall\, i,t \tag{23}$$

$$U_{i,t} + V_{i,t} \le 1 \qquad \forall\ i,t \tag{24}$$

where, $U_{i,t}$ and $V_{i,t}$ are the binary variables to guarantee the continuity of the performance periods of the controllable loads.

3.4 CHP modelling

3.4.1 Ramp rate limits

These constraints are related to the status of the CHP units at the hours t and t+1.

$$P_{i,t}^{CHP} - P_{i,t-1}^{CHP} \le (1-\alpha_{i,t}^{CHP})UR_i^{CHP} + \alpha_{i,t}^{CHP}P_{CHP}^{\min}\ \ \forall\ \ t>1 \tag{25}$$

$$P_{i,t=1}^{CHP} - P0_i^{CHP} \le (1-\alpha_{i,t=1}^{CHP})UR_i^{CHP} + \alpha_{i,t=1}^{CHP}P_{CHP}^{\min}\ \ \forall\ \ t=1 \tag{26}$$

$$P_{i,t-1}^{CHP} - P_{i,t}^{CHP} \le (1-\beta_{i,t}^{CHP})DR_i^{CHP} + \beta_{i,t}^{CHP}P_{CHP}^{\min}\ \ \forall\ \ t>1 \tag{27}$$

$$P0_i^{CHP} - P_{i,t}^{CHP} \le (1-\beta_{i,t=1}^{CHP})DR_i^{CHP} + \beta_{i,t=1}^{CHP}P_{CHP}^{\min}\ \ \forall\ \ t=1 \tag{28}$$

$$\alpha_{i,t}^{CHP} + \beta_{i,t}^{CHP} \le 1 \quad \forall\ \ t \tag{29}$$

$$\alpha_{i,t}^{CHP} - \beta_{i,t}^{CHP} = I_{i,t}^{chp} - I_{i,t-1}^{chp} \quad \forall\ \ i,t \tag{30}$$

3.4.2 Thermal operating zones of the CHPs

The allowable thermal operating zone of a CHP is shown in Fig. 1, and formulated by (31).

$$\alpha_{CHP}^{th}P_{CHP(t)} + \beta_{CHP}^{th}H_{CHP(t)} \le \gamma_{CHP}^{th}I_{i,t}^{chp} \quad th \in \{1,2,3\} \tag{31}$$

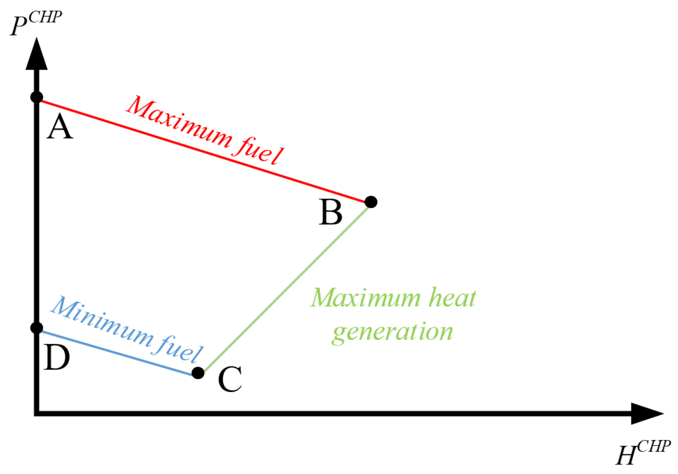

Fig. 1 Allowable thermal-electrical operating zone of CHP

3.4.3 Thermal constraint of ancillary boiler

Thermal power of the ancillary boilers should be in a predefined allowed range as indicated in (32).

$$H_B^{min} I_t^{boi} \leq H_{B(t)} \leq H_B^{max} I_t^{boi} \quad , \forall \ t \tag{32}$$

3.5 Storage modelling

A battery or storage is an electrochemical energy resource that is able to convert its stored energy to the electrical energy, everywhere and every time. Nowadays, batteries have an important role in different industries. The constraints of the storages are considered as represented in [20] and [30] that include: the maximum stored energy of the battery, and the maximum charging or discharging capabilities of the electrical storages.

3.6 Wind power modelling

The power generation of wind turbine is lower than its' installed capacity, as indicated in (33).

$$0 \leq P_{i,t}^{W} \leq P_{i,t}^{W,max} \tag{33}$$

3.7 Uncertainty modelling

There are many uncertain parameters having a severe impact on the revenue and cost. Parameters such as: load, wind speed and electricity market price. This paper assumes an hourly expected value for the electricity market price and uses Information Gap Decision Theory (IGDT) for modelling the uncertainties of wind turbine power generation and electrical load consumption.

Risk-averse strategy desires to schedule in a way to be immune against losses or low profit due to unfavorable deviations of load or wind power generation from the forecasted values. Hence, the robust performance can be written as:

$$\xi^R = max\{\xi: (\min A \geq A_e = (1-\alpha)A_0)\} \tag{34}$$

where A_e is defined as the critical profit. A_0 is defined as the expected maximum profit based on the forecasted values, if the scheduling is done solely based on forecasted parameters and risk is not taken into account; α is a profit deviation factor defined to model the minimum desirable profit of the MG. For a risk-averse MG, the objective function considering IGDT is to maximize the uncertainty variable ξ while the required performance is satisfied.

Given the uncertainty ξ^R, the minimum profit in (34) is readily seen to occur for the lowest wind power generation and highest electrical load, allowed by the IGDT model at the horizon of uncertainty ξ, which are modelled through equations (35)-(40). Hence, the above optimization problem can be simplified as follows:

$$\xi^R = \max \quad \xi \tag{35}$$

$subject\ to$:

$$\min\left\{\sum_{t=1}^{T} ep_{i,t}^{sell} P_{i,t}^{sell} - \sum_{t=1}^{T}\left(Cost_t^{CHP} + Cost_t^{boi} + Cost_t^{S} + Cost_t^{Wind} + Cost_t^{buy}\right)\right\} \geq A_e \tag{36}$$

$$\left(1+\xi_{load}\right) L_{i,t}^{E} \leq PL_{i,t}^{E} \leq Demand_{i,t}^{E} \tag{37}$$

$$0 \leq P_{i,t}^{W} \leq \left(1-\xi_{wind}\right) \overline{P}_{i,t}^{W} \tag{38}$$

$$\xi_{load}, \xi_{wind} \geq \xi \tag{39}$$

(4)-(33) (40)

The solution of the above optimization problem will give the robust schedule based on the defined value of A_e. In other words, the solution guarantees a minimum profit of A_e if all hourly absolute relative forecasted errors are less than ξ^R. Note that ξ^R is the maximized tolerable error.

Unexpected behavior of the wind speed and electrical load consumption is sometimes favorable. A risk-seeker MG desires to benefit from these favorable variations using an opportunity function. The mathematical formulation of the opportunity function can be expressed as follows:

$$\xi^O = \min\left\{\xi : \left(\max \quad A \geq A_y = \left(1+\beta\right) A_0\right)\right\} \tag{41}$$

where A_y is a target profit that MG hopes to gain in the event of low load and high wind speed situations, which is a factor of the expected profit A_0 through β. Target profit A_y is generally greater than A_e. A similar formulation can be driven for opportunity function. In fact, for a determined uncertainty factor of ξ, the maximum profit occurs in the highest wind power generation and lowest electrical load. So, the bi-level optimization of (41) is simplified to the single level optimization of (42)-(47).

$$\xi^O = \min \quad \xi \tag{42}$$

$$subject\ to: \tag{43}$$

$$\left\{ \sum_{t=1}^{T} ep_{i,t}^{sell} P_{i,t}^{sell} - \sum_{t=1}^{T} \left(Cost_t^{CHP} + Cost_t^{boi} + Cost_t^{S} + Cost_t^{Wind} + Cost_t^{buy} \right) \right\} \geq A_y$$

$$\left(1 - \xi_{load}\right) L_{i,t}^{E} \leq PL_{i,t}^{E} \leq Demand_{i,t}^{E} \tag{44}$$

$$0 \leq P_{i,t}^{W} \leq \left(1 + \xi_{wind}\right) \overline{P}_{i,t}^{W} \tag{45}$$

$$0 \leq \xi_{load}, \xi_{wind} \leq \xi \tag{46}$$

(4)-(32) (47)

Thus, if the actual power of wind turbine and electrical load deviate from their forecasted values byξ^O, a greater profit of A_y may be achieved. Note that ξ^O is the minimum required favorable uncertainties that make A_y achievable.

In order to clarify the optimization model, the flowchart of Fig. 2 is presented. It indicates the procedure of the decision-making using the IGDT-based optimization model. As can be observed, at first a deterministic model is solved including the expected values of the stochastic parameters. Then the expected profit is used to construct the profit targets of the opportunistic and robustness models.

4. Numerical results

The IEEE 33-bus standard test system is utilized to investigate the numerical results. The scheduling horizon is considered to be 24 hours. Fig. 3 shows the thermal and electrical load patterns (the electrical and thermal peak loads are about 27.9 MW and 8.8 MW, respectively). Thermal-electrical operating zone of all CHP units is similar to Fig. 1, considering A (0,4), B (2,2), C (1.33,0.66) and D (0,2). Their energy efficiency is 80%. The energy efficiency of all the boilers is 70% and they have different capacities: 1MW (boilers 2 and 3), 2 MW (boilers 1 and 7-12) and 5 MW (boilers 4-6). Energy storage unit is 1.8MW/1.8MWh, and its efficiency and initial stored energy are respectively 95% and 0.9 MWh. In addition, installed capacity of the wind turbine is 7 MW.

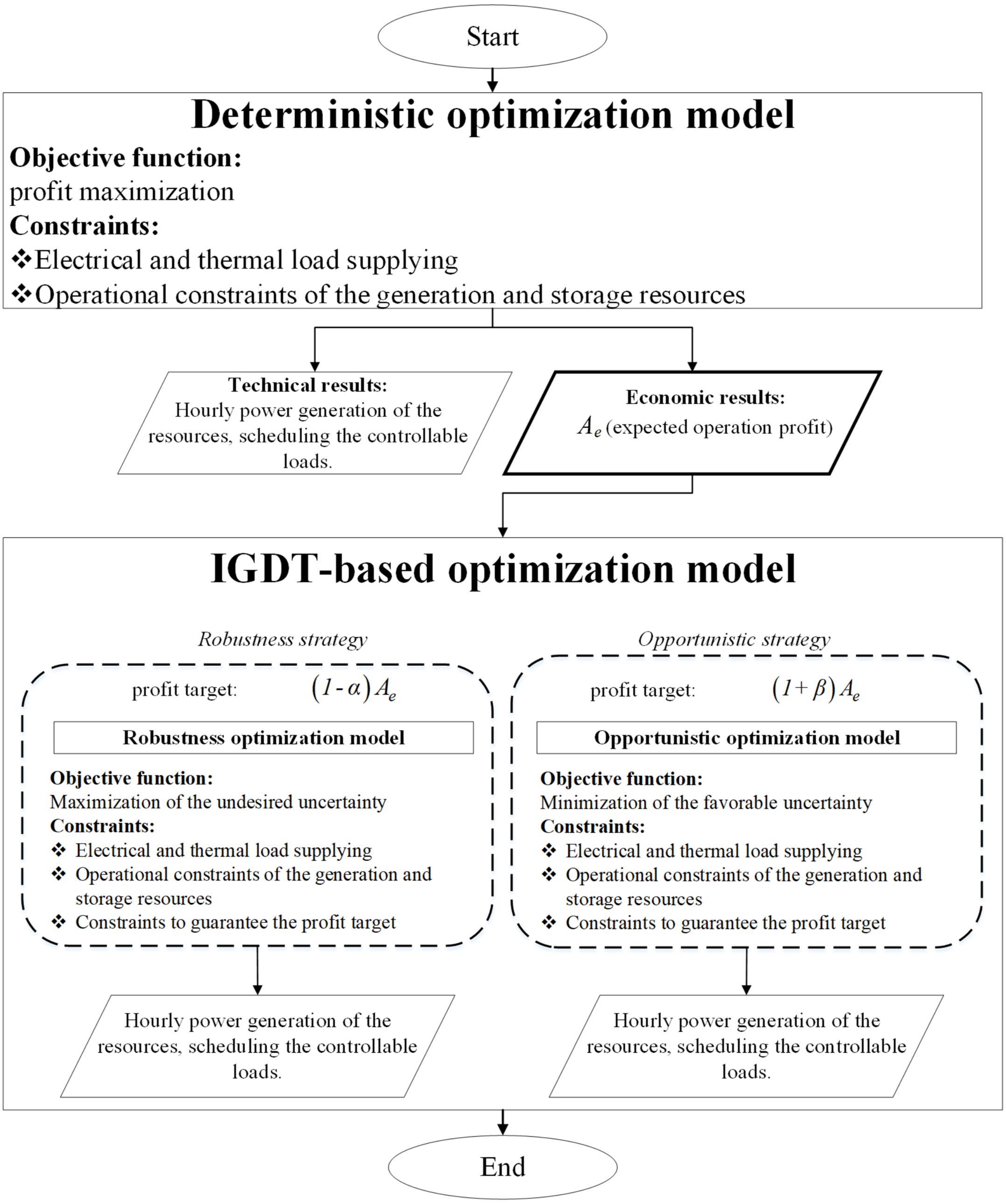

Fig. 2 Decision-making algorithm

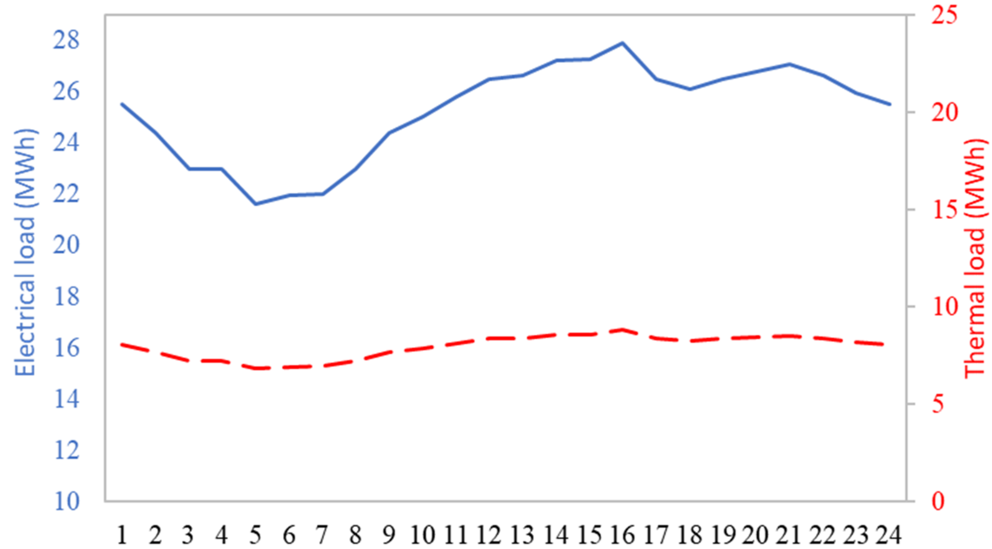

Fig. 3 Electrical and thermal load

There are a number of controllable loads in nodes 1, 5 and 8 with respectively 1, 2 and 3 (MWh) electricity consumption. They should be supplied for the 4 hours in the horizon of 18:00-24:00. Fig. 4 shows the IEEE 33-bus test system which contains CHP, boiler and wind turbines to supply the thermal and electrical loads. Hourly expected values of the wind power generation and the electricity market price are indicated in Fig. 5. Gas price is considered 0.15 ($/m^3). Heating value of gas is 8600 (kcal/m^3). So, the value of $\sigma^{MWh/m3}$ will be about 0.01 (MWh/m^3).

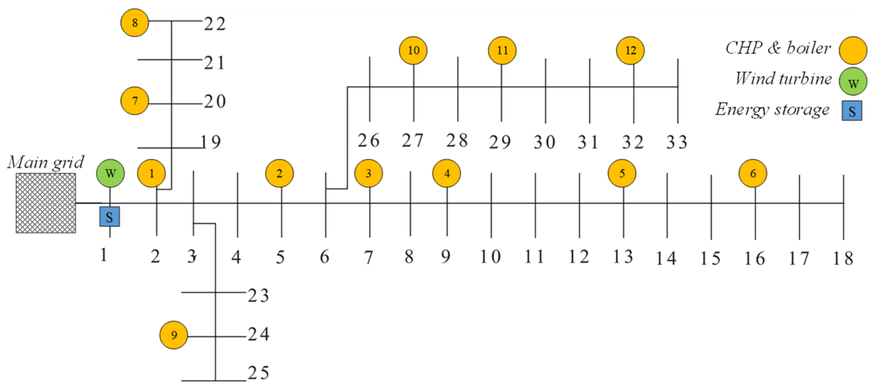

Fig. 4 IEEE 33-bus test system

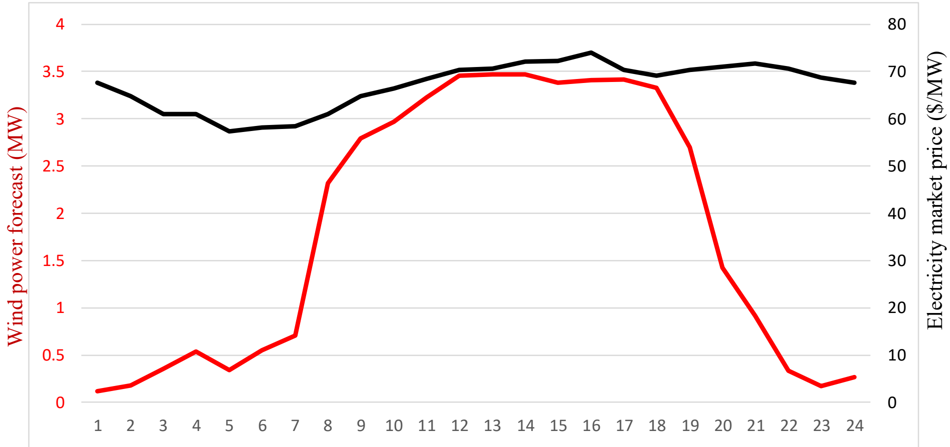

Fig. 5 Expected values of the wind power generation and electricity market price

The results and analysis of the results obtained from the implementation of the proposed method on the introduced MG is presented here. Three scenarios have been considered to perform the numerical analysis:

Scenario 1) Wind turbine does not participate in the MG scheduling.

Scenario 2) Wind turbine participates in the MG scheduling.

Scenario 3) Wind turbine participates in the MG scheduling, and the performance period of controllable loads extends to the whole operation horizon.

4.1 MG's short-term scheduling using a deterministic approach

The scheduling results are shown at the following of the paper for the introduced scenarios. As indicated in Fig. 6, in all the scenarios, MG imports electrical power from the main grid during the low electricity price periods (hours 1-11 and 24) and exports the power at the other hours. At the first horizon, CHP units generate less energy and their operating point is on the D-C section (Fig. 1). During the electricity export period, the operating point is on the A-B section. At the hours 14-16 and 21, the power consumption of the MG and the electricity price are maximum. So, CHP units should generate more electrical energy. In A-B section, generating the higher electrical power leads to the lower thermal power generation of the CHP units. The power generation of the CHPs and boilers have been respectively shown in Fig. 7 to Fig. 9. In scenario3, the controllable loads, are shifted to the hours 5, 6, 7 and 8. Because, their energy consumption during the hours 18-24 requires the higher electricity generation of the CHP units and their lower thermal power generation. Hence, boilers which have lower energy efficiency, should increase their thermal power generation and this will be a non-optimal solution. Ten CHP units are committed in scenario 1.

In scenarios 2 and 3, wind turbine which has no variable cost, generates the power and 9 CHP units are committed in all the operation horizon. In order to clarify the CHPs' behaviours, the electrical and thermal power generation of the CHP units of 9 and 11 are presented for scenario 3. As can be observed in Fig. 10, CHP9 always generates more thermal power than that of CHP11, because it should supply a greater thermal load. The daily heat consumption of different buses is indicated in Fig. 11. As indicated in Fig. 9, due to non-transferability of the thermal power between different buses, boilers have more power generation in scenarios 2 and 3. Because, in these scenarios fewer CHP units are committed. As can be observed in Table 1, if the thermal power can be transferred through an ideal thermal network, the power generation of the boilers, that have lower energy efficiency, will be reduced about 8.8%, and the CHP units will supply a greater share of the thermal load.

According to Fig. 12, in all the scenarios, storage unit is charged and discharged based on the electricity price variation. Total operation cost of the scenarios 1 to 3 are respectively 14637 $, 13822 $ and 13559 $.

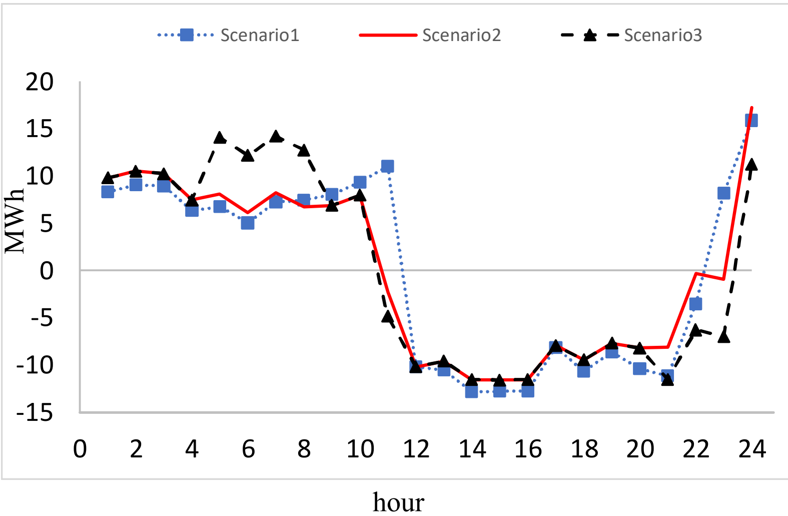

Fig. 6 Input electrical power from main grid to MG

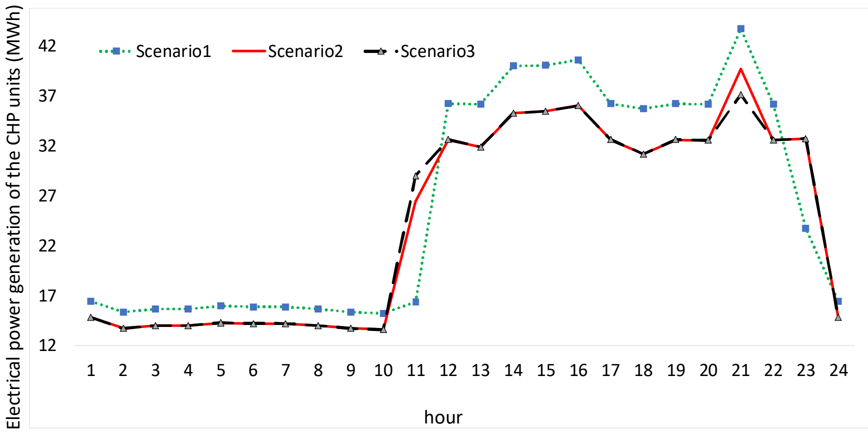

Fig. 7 Electrical power of CHPs in different hours and scenarios

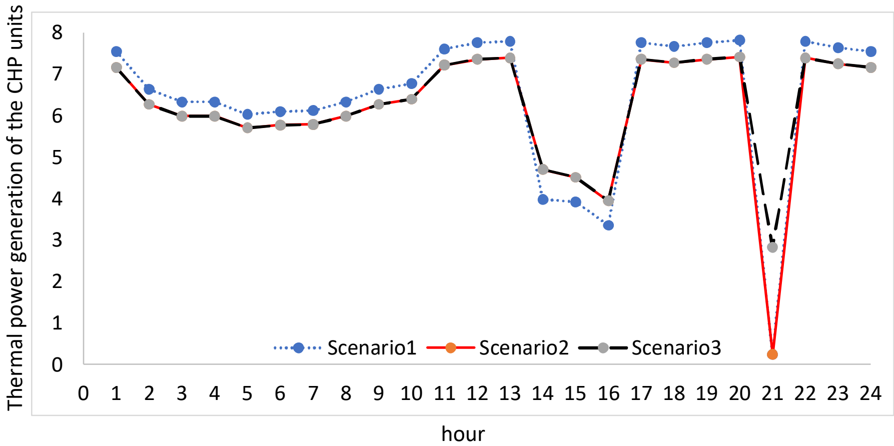

Fig. 8 Thermal power of CHPs in different hours and scenarios

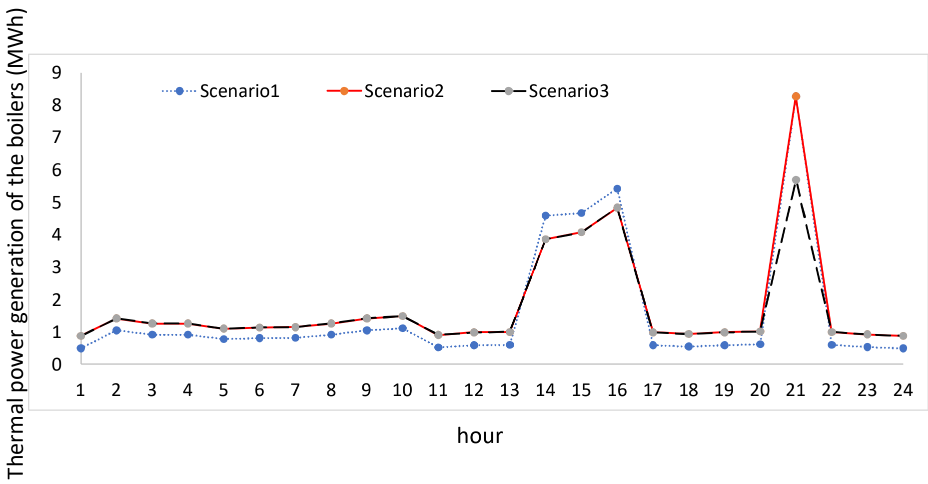

Fig. 9 Thermal power of boilers in different hours and scenarios

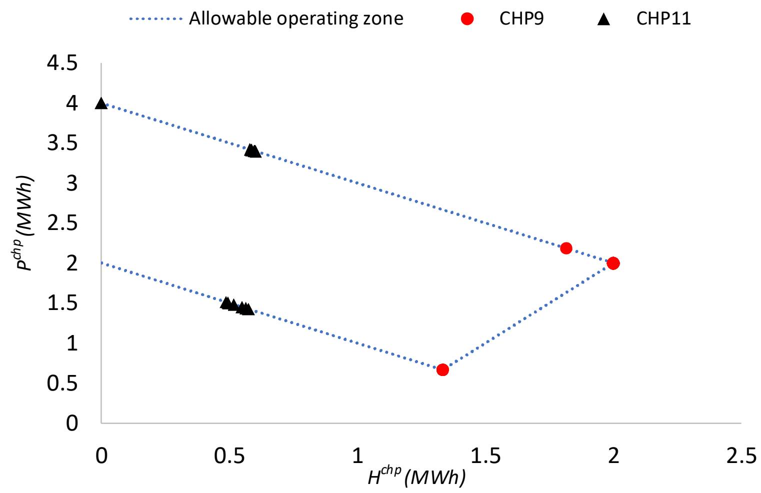

Fig. 10 Operating points of CHP9 and CHP11 during the operation horizon (scenario3).

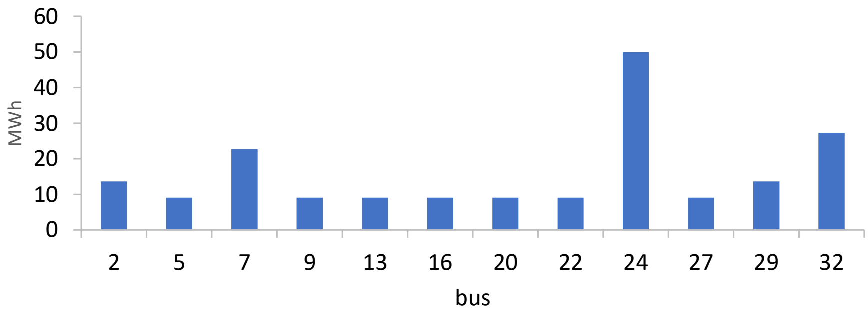

Fig. 11 The daily heat consumption of different buses

Table 1. The effect of heat transferability on the thermal power generation of the resources.

	Total thermal power of boilers	Total thermal power of CHPs	Total electrical power of CHPs
Non-transferability	40.37	150.7	587.4
Transferability	36.8	154.27	587.4

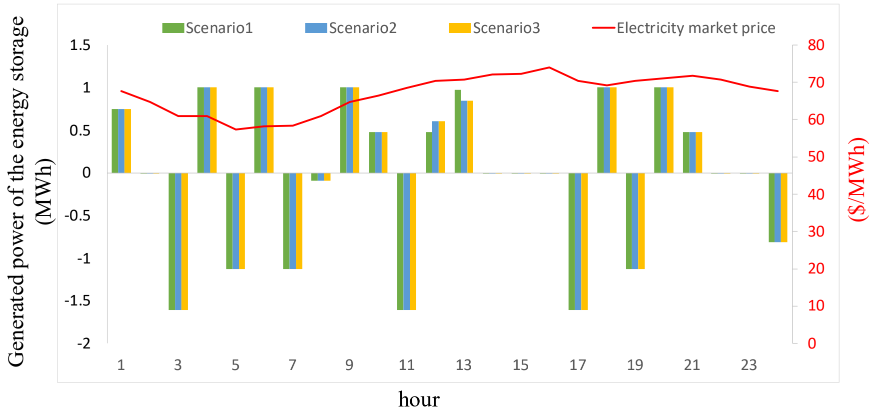

Fig. 12 Charge and discharge of storage unit at different hours

4.2 Impact of the uncertainties on the system operation cost in the IGDT-based modeling

Risk-averse and risk seeker operation strategies have different effects on the system costs as well as on the technical decisions. Fig. 13 indicates the robustness and opportunity indices (ξ) of the scenarios, considering different cost targets. In scenario 1, access to 14100$ as the cost target requires an opportunistic approach and at least 5% proper uncertainty in the load (less than predicted load). While, in scenario3, this cost target immunes decisions against the 5% unproper uncertainties of the wind power generation and load consumption. This condition can be seen in the intersection point of the curves which is depicted in the figure.

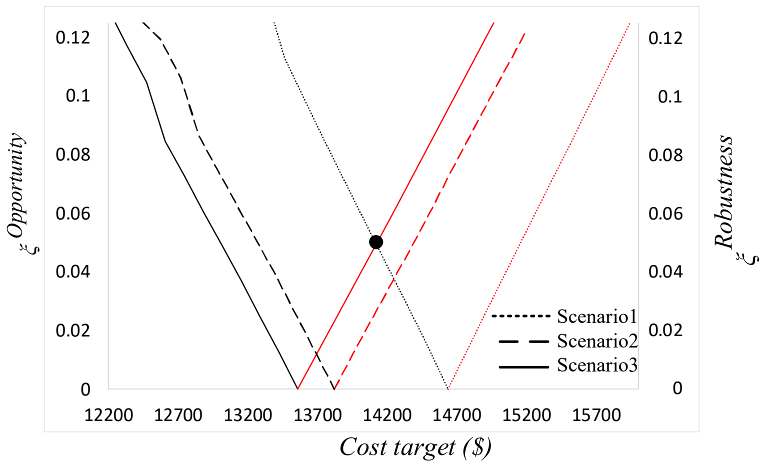

Fig. 13 Robustness and opportunity indices in different scenarios

Fig. 14 and Fig. 15 indicate the robustness and opportunity indices in different assumptions, when all of the uncertain parameters are included or only one of them is considered. According to the indicated figures, the load uncertainty is more important in comparison to the wind power generation. For example, if the cost target is increased about 6% in comparison to the expected cost, the scheduling will be fully immune against the wind power uncertainty. While in such a situation, decisions are robust against the load uncertainty up to about 7%. This analysis indicates the importance of the different uncertain parameters. It is clear that the minimum cost target which can be reached through the wind power uncertainty is about 12760 $. In fact, a risk seeker can reduce the operation cost by up to 5.8% using the opportunity of wind power uncertainty. While this target cost can be earned in an opportunistic approach for the favorable demand uncertainty of about 8%.

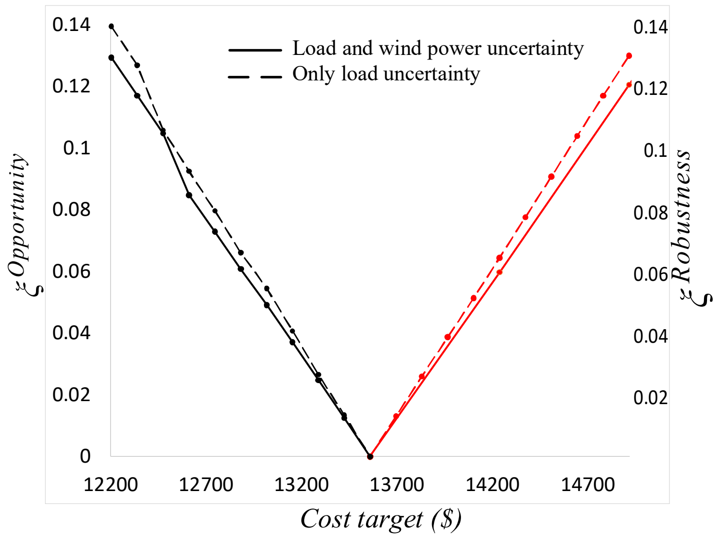

Fig. 14 The effect of load uncertainty on the operational cost

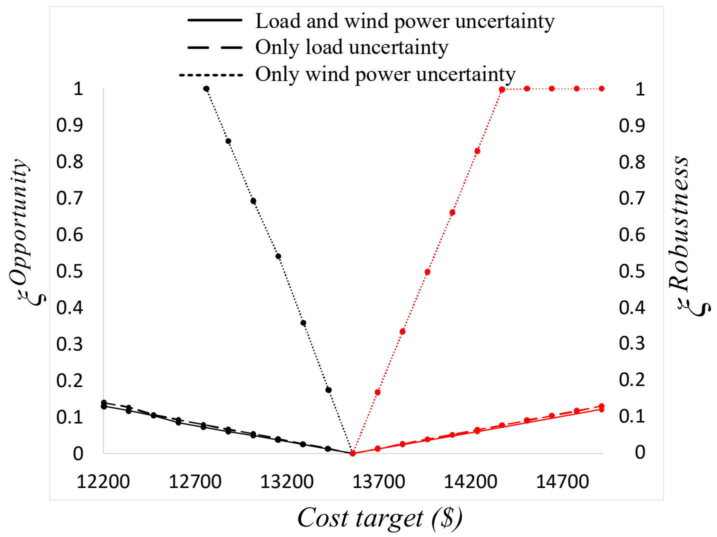

Fig. 15 The effect of different uncertainties on the operational cost

4.3 Short-term scheduling in the IGDT-based modeling

The technical aspects of different strategies are indicated in Fig. 16 - Fig. 18, for cost targets of 17627 $ and 9491 $. As indicated in Fig. 16 and Fig. 17, in the robust scheduling, CHP units increase their electrical power generation and wind turbine has the lower participation in the load supplying. In fact, this is the best decision in the worst case, when the load and wind speed have respectively very high and very low values.

Considering the allowed operational zone of the CHP units, their thermal power generation should be reduced in some hours as indicated in Fig. 18. So, the ancillary boilers supply the entire thermal load. In an opportunistic strategy, where electrical load is low and wind speed is high, wind power generation is increased and the CHP units have the lower share in the electrical load supplying.

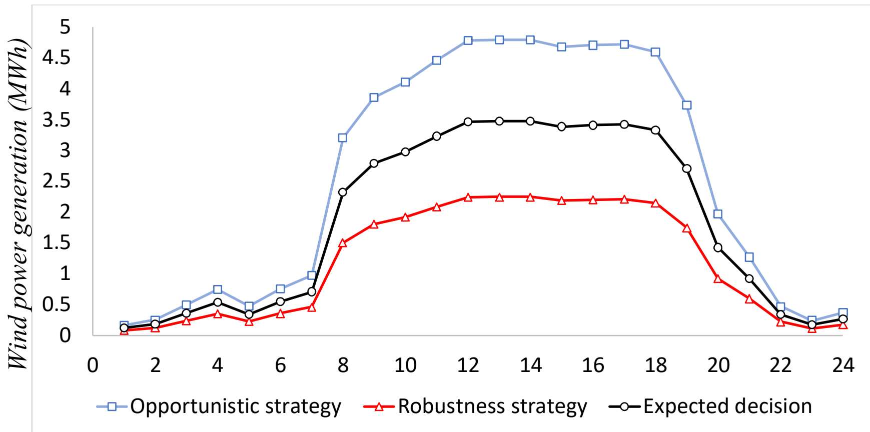

Fig. 16 Wind power generation curve for robustness and opportunistic strategies, respectively with cost targets of 17627 $ and 9491 $

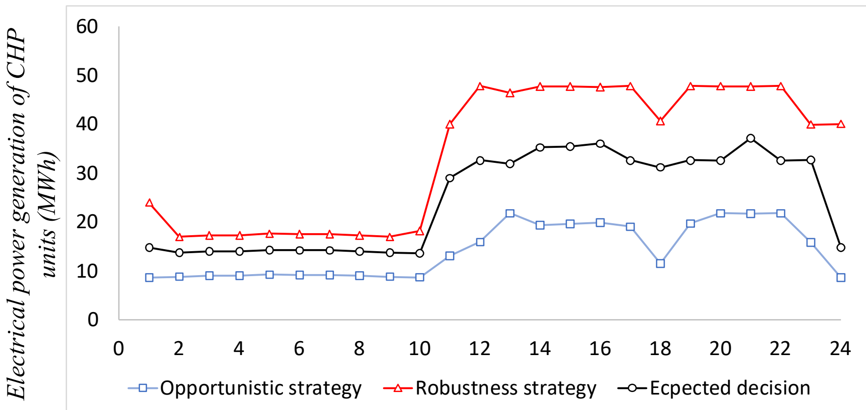

Fig. 17 Electrical power curve of CHPs for robustness and opportunistic strategies, respectively with cost targets of 17627 $ and 9491 $

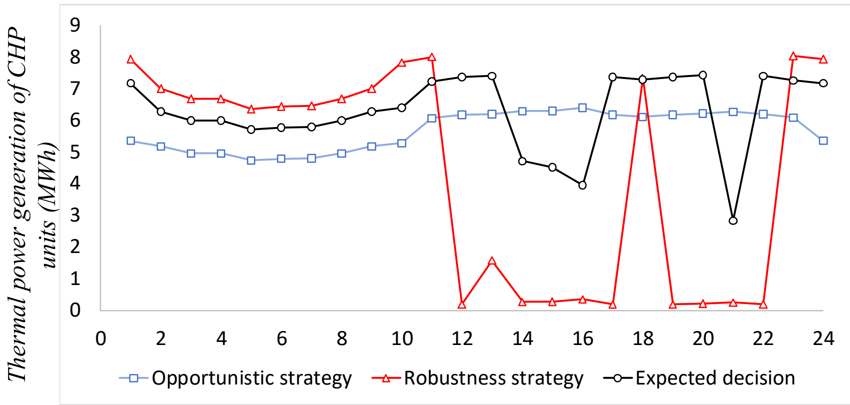

Fig. 18 Thermal power curve of CHPs for robustness and opportunistic strategies, respectively with cost targets of 17627 \$ and 9491 \$

4.4 Verifying the results by Monte-Carlo simulation method

As indicated in Fig. 19, to identify the performance of the proposed uncertainty modelling, multiple scenarios are generated using the Weibull and normal distribution functions respectively for the wind power and electrical load. It has to be proven that, decisions in the robustness strategy or opportunity strategy have the superiority to the decisions related to each scenario in the indicated test regions. The cost targets of 10386 \$ and 15822 \$ are respectively considered for the opportunistic and robustness strategies. These values correspond to $\xi^{Robustness} = \xi^{Opportunity} = 0.2$. 2500 scenarios are generated which 2352 of them are in the test regions. Histogram of the operation costs of these scenarios is indicated in Fig. 20. It is obvious that, the operation costs of all scenarios are lower than 15822\$ and greater than 10386\$. So, decisions made in the opportunistic and robustness strategies guarantee well the operation cost against the uncertainties lower than 20%.

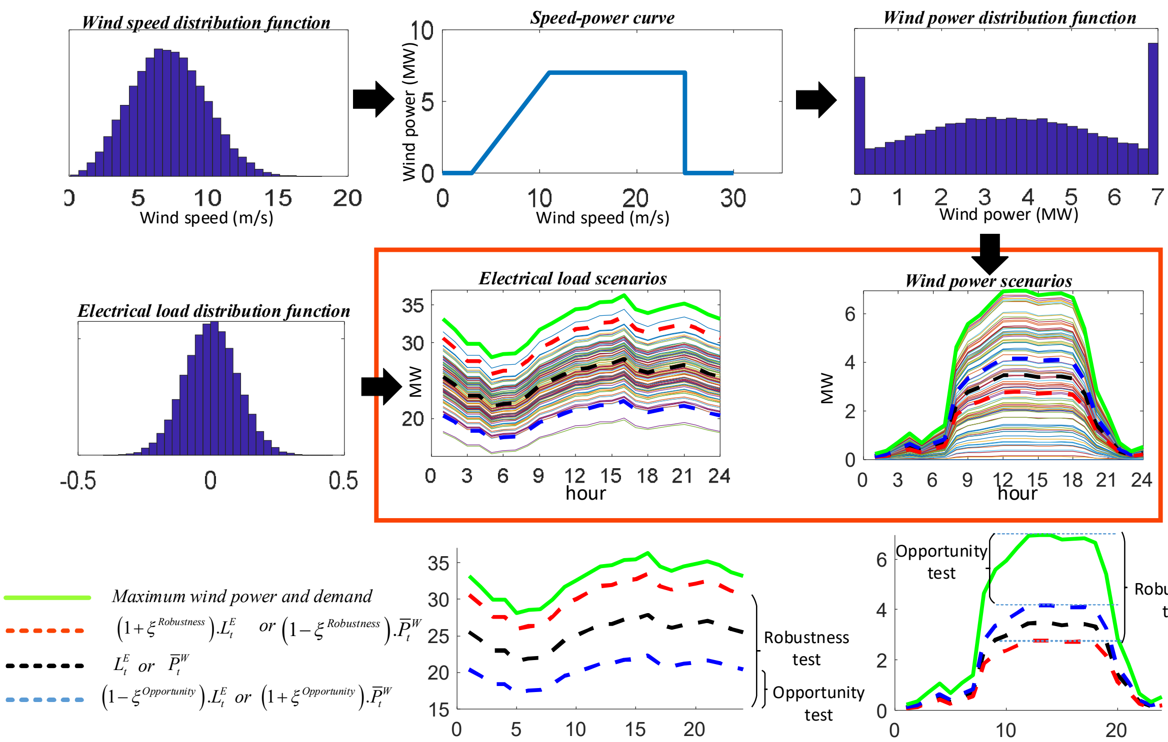

Fig. 19 Scenario generation for Monte-Carlo simulation to test the results of the IGDT method

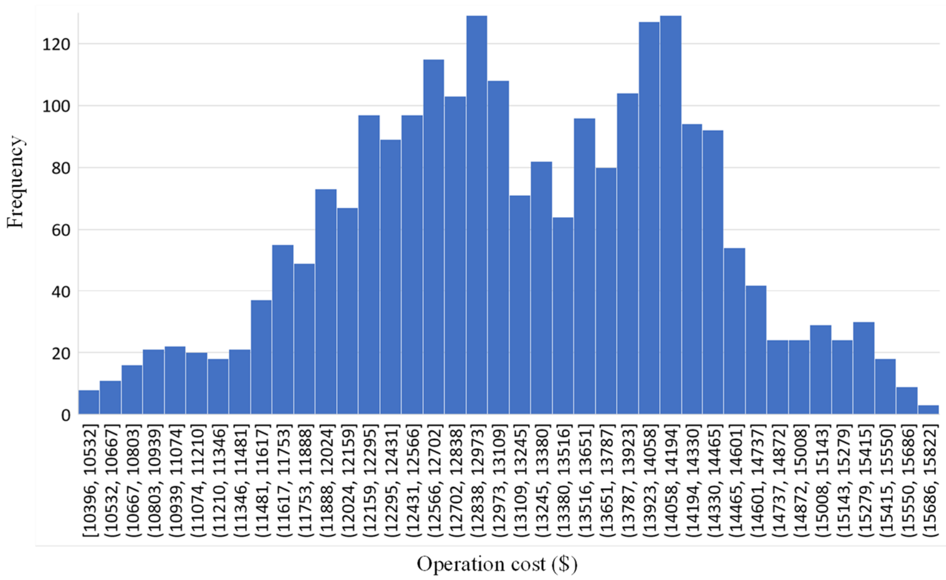

Fig. 20 Histogram of the operational cost, considering the different realization of the uncertainties

5. Conclusion

According to the high penetration of DERs and MGs in the structure of the power system, this paper proposed a framework for the short-term operation of MGs. Different resources such as wind turbines, CHP units, energy storages, boilers and the main electricity grid are considered in order to supply the electrical and thermal loads. Different uncertainty resources such as wind speed and load forecast can affect the operational decisions. In this paper, an IGDT-based optimization model is proposed for decision making under different uncertainties. Although the wind turbine has a high capacity of 7 MW, wind power uncertainty has a lower impact on the system costs compared to the load uncertainty. In fact, the favorable wind power uncertainty is able to reduce the operation cost up to 5.8%, while this target cost is earned in an opportunistic approach for the favorable demand uncertainty of about 8%. Although the allowed operation zone of CHP decreases the dependency of its electrical output to the thermal power generation, CHP units increase their electrical power generation when the electricity price is high. In these hours, their thermal power generation is forced to decline and boilers generate more thermal power. Monte-Carlo simulation used about 2350 combined scenarios of the wind speed and electrical load in the test regions of the IGDT strategies. These scenarios are related to the maximum uncertainty of 20%. In fact, the operation costs of these scenarios are lower than the cost target of the robust strategy and higher than the cost target of the opportunistic strategy.

Acknowledgment

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