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Modeling the risk-based decisions of the microgrid in day-ahead energy and reserve markets considering stochastic dispatching of electrical and thermal energy storages

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ABSTRACT

In this paper, the electrical and thermal energy management problem of a micro-grid operator (MGO) is addressed under uncertainties aiming at participating in the day-ahead energy and reserve markets. For this purpose, a robust two-stage stochastic model is developed to protect the first stage MGO's decisions, i.e., its bids in the energy and reserve markets, against the uncertainty of the real-time energy market price. This is done through stochastic dispatching of the MG resources which includes the electrical and thermal energy storages and the combined heat and power unit as the second-stage decisions. The results showed that the MGO's expected total cost decreases when it participates in both the energy market and the reserve market in comparison with the case it only participates in the energy market. Also, the risk-based behavior of the MGO showed that increasing the robust parameter decreases the reserve provided for the market and the net power trading with the market. However, the proposed robust two-stage stochastic model leads to a smaller reduction of the MGO's first-stage decisions in the worst case in comparison with the conventional methods, i.e. deterministic and probabilistic ones. This issue proves the effectiveness of the proposed approach to protect the MGO's decisions against the uncertainties.

1. Introduction

1.1. Background and motivation

The local consumers' electrification and thermal energy supply through the distributed energy resources (DERs) play vital roles in improving the economic, environmental, and technical indices in the energy systems. For this purpose, these resources are integrated under the management of the micro-grid operator (MGO). The MGO supplies the required energy demand of the micro-grid (MG) through importing energy from the energy market and determining the optimal energy scheduling of its DERs. In addition, the characteristics of some resources such as the electrical energy resources (EESs) give the ability to the MGO to provide ancillary services such as the reserve capacity for the market. Accordingly, appropriate formulations are required to model the MGO's decisions to schedule its resources to supply local energy demand and also to contribute to the wholesale reserve and energy markets. Also, when the reserved capacity of the MGO to the market is deployed in the real-time (RT) operation, the MGO receives a revenue regarding the RT energy market price. Therefore, the uncertainty of the RT price in the market has a significant effect on the MGO's decisions especially in providing the reserve capacity for the market. To model this uncertainty, the MGOs' problem can be solved as a risk-based optimal scheduling challenge to protect the MGO's decisions against the uncertainties.

1.2. Literature review and contributions

The MGO's participation in the markets, as well as its energy management (EM) problem, are addressed in many studies. A two-stage stochastic model is proposed in [1] to investigate the EM problem of a MGO with renewable energy sources (RESs) and responsive load. The EM problem of a MG is formulated in order to minimize the cost of operation and the pollution emission in [2] where the stochastic

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Nomenclature

Acronyms

CHP	Combined heat and power
DA	Day-ahead
EES	Electrical energy storage
EMS	Energy management system
IL	Interruptible load
MG	Micro-grid
MGO	Micro-grid operator
PV	Photovoltaic
RT	Real-time
TES	Thermal energy storage

Parameter

$\underline{E}^{EES}/\underline{E}^{TES}$	Minimum stored energy in EES/TES (kWh)
$\overline{E}^{EES}/\overline{E}^{TES}$	Maximum stored energy in EES/TES (kWh)
$E^{EES.ini}/E^{TES.ini}$	Initial stored energy in EES/TES (kWh)
$ED_{s.t}$	Electrical demand (kW)
k	Reserve calling probability (%)
$\overline{P}^{CHP}$	Maximum power of CHP (kW)
$\overline{P}^{(EES_ch)}/\overline{P}^{(TES_ch)}$	Maximum power for charging of EES/TES (kW)
$\overline{P}^{(EES_dch)}/\overline{P}^{(TES_dch)}$	Maximum power for discharging of EES/TES (kW)
$\overline{P}^{IL}$	Maximum capacity of load curtailment (kW)
$P_{s.t}^{PV}$	PV power generation (kW)
$\overline{P}^{grid}$	Maximum power trading with the main grid (kW)
TD_t	Thermal demand (kW)
β	Converting factor to produce energy through consuming gas (m^3/kW)
Γ	Robustness parameter
η^{CHP_E}	Electrical energy efficiency of CHP (%)
η^{CHP_T}	Thermal energy efficiency of CHP (%)
$\eta^{EES\_ch}/\eta^{EES\_dch}$	EES's efficiency for charging/discharging (%)
$\eta^{TES\_ch}/\eta^{TES\_dch}$	TES's efficiency for charging/discharging (%)
η^{grid}	Efficiency of power trading with the main grid (%)
λ_t^{gas}	Natural gas price (\$/m^3)
λ^{PV}	Bids of PV's owner (\$/kWh)
λ^{EES}	Energy bid of EES's owner (\$/kWh)
λ^{EES_R}	Energy bid of EES's owner for providing reserve (\$/kWh)
λ^{TES}	Energy bid of TES's owner (\$/kWh)
λ_t^{IL}	Interrupted load price (\$/kWh)
λ_t^{EM}	Day-ahead energy market price (\$/kWh)
λ_t^{RT}	Real-time market price of energy (\$/kWh)
λ_t^{RM}	Reserve market price (\$/kWh)
$\overline{\lambda}_t^{RT}/\underline{\lambda}_t^{RT}$	Maximum/minimum amount of RT energy market price (\$/kWh)
ρ_s	Each scenario's probability

Variables

$B_{s.t}^{EES}/B_{s.t}^{TES}$	Binary variables used for EES/TES
B_t^{grid}	Binary variable for trading power with grid
C^E	Cost of exchange energy with the main grid (\$)
C^{CHP}	Cost for purchased energy from CHP (\$)
C^{PV}	Cost for purchased electricity from PV (\$)
C^{EES_E}	Cost of charging/discharging of EES (\$)
C^{EES_R}	Cost of reserve provided by EES (\$)
C^{TES}	Cost of charging/discharging of TES (\$)
C^{IL_E}	Cost of IL to provide energy (\$)
C^{IL_R}	Cost of IL to provide reserve (\$)
ETC	Expected total cost (\$)
$E_{s.t}^{EES}$	The energy stored in EES (kWh)
$E_{s.t}^{TES}$	The energy stored in TES (kWh)
$p_{s.t}^{gas}$	The gas consumption (m^3)
$p_{s.t}^{CHP\_E}$	CHP's electrical power (kW)
$p_{s.t}^{CHP\_T}$	CHP's thermal power (kW)
$p_{s.t}^{EES\_ch}$	The electrical charging power of EES (kW)
$p_{s.t}^{EES\_dch}$	The electrical discharging power of EES (kW)
$p_{s.t}^{TES\_ch}$	The thermal charging power of TES (kW)
$p_{s.t}^{TES\_dch}$	The thermal discharging power of TES (kW)
$p_t^{EES\_R}$	The reserve provided by EES (kW)
$p_t^{grid\_in}$	The purchased power from the market (kW)
$p_t^{grid\_out}$	The sold power to the market (kW)
p_t^{IL}	The interrupted load (kW)
$p_t^{IL\_R}$	The reserve provided by IL (kW)
$p_t^{MG\_R}$	Reserve provided by the MGO to the market (kW)
TC^{FD}/TC^{SD}	Total cost of the first/second stage decisions (\$)
$\xi_t.y$	The auxiliary variables used in the robust optimization model
$RETC$	Robust expected total cost (\$)
R^R	Revenue of MGO from providing reserve for the market (\$)
$Z.q_t$	The dual variables in the model of robust optimization

behavior of the demand, RESs, and the energy price are formulated through the Monte Carlo simulation. The MGO's bids in the day-ahead (DA) market are determined with the demand side management using a hybrid methodology in [3]. The EM optimization problem of a combined cooling, heating, and power (CCHP) MG is mathematically modeled as a robust-stochastic model in [4] where the MGO trades energy with the DA market. The participation of a MGO in the regulation market through the optimal scheduling of the plug-in vehicles and the shiftable loads is addressed in [5]. The MGO's operation problem is modeled in [6] where the MGO participates in both RT and DA markets. To manage the uncertainties of the RESs and the energy prices, a bi-level model is developed. A model predictive control method is developed in [7] to formulate the EM problem of a MG equipped with photovoltaic (PV), electrical energy storage (EES), and the distributed generation (DG) to participate in the ancillary service markets. The authors of [8] proposed a stochastic EM model for the MGO's participation in the energy market. The MGOs' participation in the DA energy market is modeled using a hybrid approach in [9] considering the cooperative energy trading among the MGs. A two-stage stochastic programming approach is presented to model the participation of a MGO in the DA energy market considering the demand response programs (DRPs) in [10]. The uncertainties of the output power of RESs and the demand are modeled in the MGO's decision problem in the DA energy market using a robust two-stage stochastic model in [11]. The participation problem of a MG equipped with the electric vehicles in the DA energy market is formulated through a two-stage robust optimization problem in [12] to address the uncertainty of the market price. The DA energy management problem of a RES-based MG is modeled as a scenario-based model in [13] to manage the uncertainties.

The bidding strategies of the MGO in the markets are modeled in [14] where the uncertainties of the energy price and the RESs are applied using a robust model of optimization. A two-level EM framework is developed for the MGO's contribution to the DA market under the uncertainty of RESs in [15]. A risk-based framework is proposed in [16] to investigate the uncertainty of the RESs in the scheduling problem of energy and reserve in a MG. The MGO's participation in the DA energy and reserve markets has been addressed with the help of a hybrid methodology in [17]. The MGO's participation problem in the energy and reserve markets- considering the incentive-based DRPs- is modeled as a multi-objective optimization problem in [18]. A robust optimization approach is developed in [19] to model the MGO's strategies to participate in the DA energy and reserve markets. A two-stage stochastic programming approach is formulated in [20] to model the bidding strategy of a MGO in the DA energy and reserve markets taking the RT energy market into account. The participation of a hydrogen-based MG in the DA energy and reserve markets as well as its decisions in the RT market is presented in [21].

The EM problem of a MG consisting of PV, wind turbine (WT), and solar thermal collectors is modeled in [22] where the MGO contributes to the market through the optimal controlling of the EES and the thermal demands. In [23], the operation problem of a multi-energy MG is defined through a temporally-coordinated approach with the aim of participating in the energy markets. The CCHP units, the power to thermal conversion units, and the TESs are scheduled in the DA operation and the deviation related to the DA decisions is compensated through the battery storages in the intra-day operation step. The market participation problem of a multi-energy MG is modeled in [24], as a robust optimization problem in order to address the uncertainties.

Reviewing the previous studies showed that there are two main types of models proposed for the EM problem of the MGs besides the MGO's participation in the markets. In the first type, the MGO only supplies the electrical energy demand and it participates in the energy market [1–4,6,8–13,15] or the energy and ancillary service markets [5,7,16–21]. In the second type, the MGO supplies its electrical and thermal energy demands and it only participates in the energy markets [22–24]. Although the EM problem of the MGO in both types of models are investigated in the existing studies, there are still several research gaps that should be dealt with such as follows:

- In most of the previous studies, the MGO's participation problem in the markets is addressed where the MGO only supplies the electrical energy demand. However, modeling the MGO's decisions in the markets where the MGO supplies both the electrical and the thermal energy demands is investigated in few studies [22–24].
- Although the MG's resources such as the energy storages give the ability to the MGO to provide the reserve capacity for the market, this issue is not addressed in [22–24]. These studies have investigated the MGO's participation merely in the energy market.
- The MGO's decisions in the DA markets, like the reserve capacity for the market, does depend on the RT energy market price. Therefore, the uncertainty of this parameter causes the MGO to face major risks in its DA decisions in the market. The previous studies [22–24] have not modelled this uncertainty through an appropriate approach to obtain a robust objective function for the MGO in the worst case.

To cover the abovementioned gaps, a robust two-stage stochastic framework is proposed in here to model the MGO's decisions in the DA energy and reserve markets besides its decisions for the local electrical and thermal energy supply. In this framework, the stochastic behavior of the electrical demand and the generated power of the PV system are modeled using some generated scenarios and leading to formulating the MGO's problem as a two-stage stochastic model. Then, the uncertainty of the RT energy price is modeled through reformulating the model as a robust two-stage optimization model. This framework optimizes the DA energy and reserve bids of the MGO in the markets as the first-stage decisions through stochastic decisions of the MGO on the EES, combined heat and power (CHP) unit, and thermal energy storage (TES) (second-stage ones). Thus, the key contributions of this study are summarized as:

- Modeling the MGO's decisions in the DA energy and reserve markets when it supplies both the electrical and the thermal energy demands of the MGs.
- Proposing a robust two-stage stochastic approach to model the uncertainties in the MGO's problem. The two-stage stochastic model optimizes the MGO's bids in the DA markets of energy and reserve through stochastic decisions on the EES, TES, and CHP. Also, the aim of the robust model is to optimize the MGO's decisions in the DA markets in the worst case to consider the uncertainty of the RT market price. As a result, the proposed robust two-stage model can protect the MGO's decisions in the DA markets against the uncertainty through stochastic decisions on the EES, TES, and CHP.

1.3. Paper's structure

The organization of the other sections of this paper is as follows. In section 2, the MGO's decision problem is described. The formulation of this problem is shown in section 3. Results are presented in section 4, and the conclusion is described in the last section.

2. Problem description

In this paper, the MGO's decisions to contribute to the DA markets of energy and reserve, and to supply its local energy demands are optimized considering the uncertainties. The MG's main components are CHP, PV, EES, TES, and the electrical and thermal loads as shown in Fig. 1. The EES and the PV provide electrical energy for the system. The TES provides thermal energy for the MG. The TES is a technology to temporarily store the thermal energy at low or high temperatures with the aim of using it in other hours. Details of the performance of the TESs and their different technologies are described in [25]. The CHP unit can provide both the electrical and the thermal energy. Also, the interruptible loads (IL) and the EES have the ability to provide the reserve capacity for the MG. The MGO's decision framework is described in Fig. 2. The price bids of the CHP, PV, EES, TES, and IL besides their technical constraints are sent to the MG central control (MGCC). Then, the MGCC sends this data besides the forecasted energy and reserve price, as well as the PV power generation to the energy management system (EMS).

The MGO's problem is mathematically formulated under the uncertainties in the EMS. The uncertainties are modeled through two approaches. In the first one, the appropriate probability distribution functions (PDFs) have been employed to generate some scenarios to create the uncertainties of the electrical demand and the generated power of the PV system. In this case, a two-stage stochastic method is used to create the MGO's problem under uncertainty. In the second approach, the uncertainty of the RT price of energy is formulated through the robust approach. For this purpose, the obtained two-stage stochastic model is reformulated as a robust one. In the resulted model, the first-stage decisions are the amount of traded energy of the MGO with the market and the provided reserve to the related market, i.e., the MGO's bids in the markets. Optimal dispatching of the EES, TES, and the CHP are considered as the stochastic decisions (second-stage ones). The resulted model is solved in the GAMS software to obtain the decision variables. Then, the obtained variables are sent to the MGCC to send the bids to the market, and it sends dispatching signals to the MG's resources. The mathematical modeling of the MGO's problem used in its EMS is presented in the next section.

3. Problem formulation

The MGO's decision-making problem is formulated in this section.

3.1. Objective function

The model's objective function is to minimize the expected total cost (ETC), and it is described by:

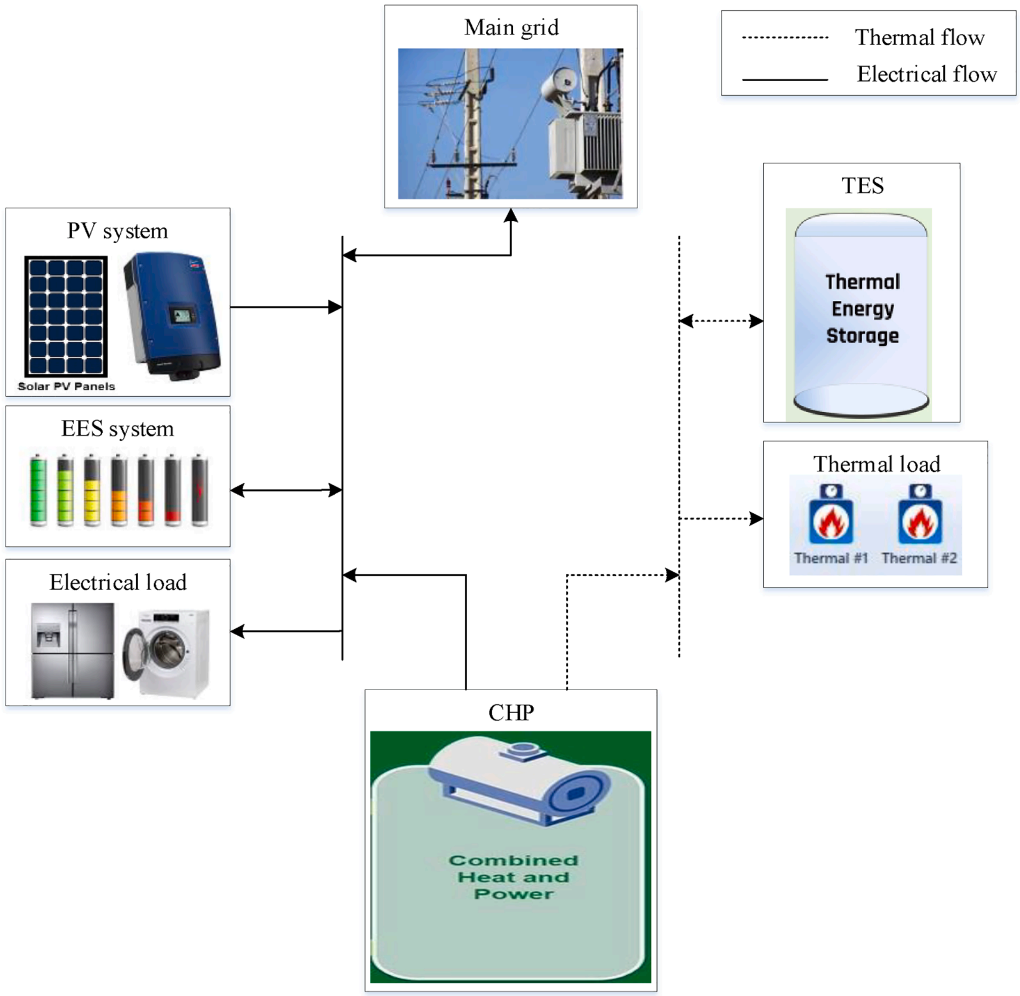

Fig. 1. Schematic of the proposed MG and its component.

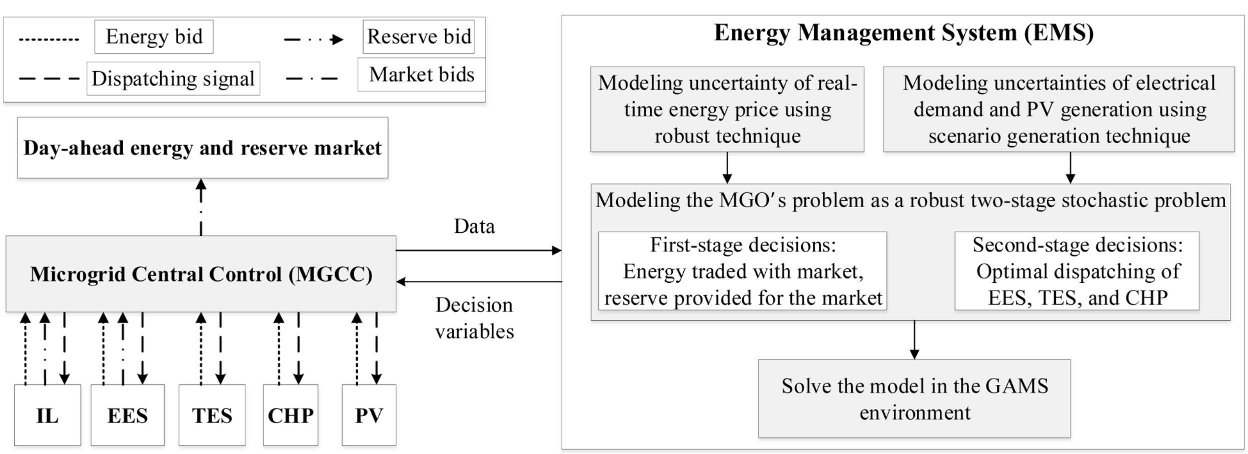

Fig. 2. The procedure of the MGO's decision-making in the DA energy and reserve market.

$$ETC = \sum_{t=1}^{T} TC^{FD} + \sum_{s=1}^{S}\sum_{t=1}^{T} \rho_s TC^{SD} \tag{1}$$

$$TC^{FD} = \left[C^{E} + C^{IL\_E} + C^{IL\_R} + C^{EES\_R} - R^{R}\right] \tag{2}$$

$$TC^{SD} = \left[C^{CHP} + C^{PV} + C^{EES\_E} + C^{TES}\right] \tag{3}$$

$$C^{E} = \lambda_t^{EM}\left(p_t^{grid\_in} - p_t^{grid\_out}\right) \tag{4}$$

$$C^{IL\_E} = \lambda_t^{IL} p_t^{IL} \tag{5}$$

$$C^{IL\_R} = \frac{1}{3}\lambda_t^{IL} p_t^{IL\_R} + \lambda_t^{IL} p_t^{IL\_R} k \tag{6}$$

$$C^{ESS\_R} = \frac{1}{3}\lambda^{EES\_R} p_t^{EES\_R} + \lambda^{EES} p_t^{EES\_R} k \quad (7)$$

$$R^R = \left[\lambda_t^{RM} p_t^{MG\_R} + \lambda_t^{RT} p_t^{MG\_R} k\right] \quad (8)$$

$$C^{CHP} = \lambda_t^{gas} p_{s.t}^{gas}, p_{s.t}^{gas} = \left(p_{s.t}^{CHP\_T}\beta\right)/\eta^{CHP\_T} \quad (9)$$

$$C^{PV} = \lambda^{PV} P_{s.t}^{PV} \quad (10)$$

$$C^{EES\_E} = \lambda^{EES}\left(p_{s.t}^{EES\_dch} - p_{s.t}^{EES\_ch}\right) \quad (11)$$

$$C^{TES} = \lambda^{TES}\left(p_{s.t}^{TES\_dch} - p_{s.t}^{TES\_ch}\right) \quad (12)$$

The ETC is modeled in Eq. (1) which includes two terms where the first and the second terms model the cost of the first-stage (independent from scenarios) and the second-stage decisions, respectively. The first stage's cost decisions are modeled in (2) using five parts. The first part of (2) models the cost of exchanging power with the energy market presented in (4). The cost on ILs which is shown as the second part of (2) is modeled in (5). The third part of (2) is described in (6) which shows the cost of providing reserve capacity by the ILs and the cost of providing energy when this capacity is deployed in the RT operation. The fourth part of (2), presented as (7), is used to model the cost of providing the reserve capacity to the MGO by the EES and its related cost in the RT operation when the reserve capacity is deployed. The last part of (2) is the MGO's revenue from providing the reserve capacity and the related energy when the reserve capacity is deployed in the RT operation, i.e. the first and second parts of (8), respectively.

The second term of (1) is modeled as (3) using four parts. The first part is the cost of purchased energy from the CHP unit which is modeled as (9). The cost of purchased energy from the PV system which is formulated in (10) is the second part of (3). The third and the fourth parts of (3) are used to model the cost of the EES and the TES to provide energy for the MGO as described in (11) and (12), respectively.

3.2. *Technical constraints:*

The ETC of MGO is minimized considering the following constraints.

- **Energy and reserve balance constraints**

The balances of the electrical and the thermal energy in the MG are modeled in (13) and (14), respectively. The purchased power from the main grid, the electrical output power of the CHP, the generated power of the PV arrays, the discharging power of the EES, and the amount of the IL are assumed as the supply side of (13). The provided energy in the supply side is used to supply the electrical demand of the MG, to charge the EESs, and to sell energy to the grid. The balance of the thermal energy in the MG is modeled in (14). The reserve provided by the MGO for the market is provided by the EES and IL as shown in (15).

$$\begin{aligned} &p_{s.t}^{CHP\_E} + P_{s.t}^{PV} + p_t^{IL} + p_{s.t}^{EES\_dch} + \left(p_{s.t}^{grid\_in}\eta^{grid}\right) \\ &\quad = p_{s.t}^{EES\_ch} + \left(p_t^{grid\_out}/\eta^{grid}\right) + ED_{s.t} \end{aligned} \quad (13)$$

$$p_{s.t}^{CHP\_T} + p_{s.t}^{TES\_dch} = p_{s.t}^{TES\_ch} + TD_t \quad (14)$$

$$p_t^{MG\_R} = p_t^{IL\_R} + p_t^{EES\_R} \quad (15)$$

- **CHP constraints**

The CHP's technical constraints are formulated in (16) and (17). The electrical and the thermal energy output of the CHP are positive variables and the sum of these variables should be smaller than or equal to the CHP's maximum capacity as modeled in (16). The relation between the electrical and the thermal energy produced by the CHP is modeled as (17) [26].

$$p_{s.t}^{CHP\_E} \geq 0.p_{s.t}^{CHP\_T} \geq 0.p_{s.t}^{CHP\_E} + p_{s.t}^{CHP\_T} \leq \overline{P}^{CHP} \forall t \in \mathrm{T} \quad (16)$$

$$p_{s.t}^{CHP\_E} = p_{s.t}^{CHP\_T}\left(\eta^{CHP\_E}/\eta^{CHP\_T}\right) \forall t \in \mathrm{T} \quad (17)$$

- **Constraints of power trading with the main grid**

The MG's technical constraints to trade energy with the main grid are modeled in (18)-(21).

$$p_t^{grid\_out} + p_t^{MG\_R} \leq \overline{P}^{grid} \quad (18)$$

$$p_t^{grid\_in} \leq \overline{P}^{grid} B_t^{grid} \quad (19)$$

$$p_t^{grid\_out} \leq \overline{P}^{grid}\left(1 - B_t^{grid}\right) \quad (20)$$

$$p_t^{grid\_in}.p_t^{grid\_out}.p_t^{MG\_R} \geq 0 \quad (21)$$

- **EES's constraints**

The technical constraints of the EES to provide energy and reserve are described in (22)-(29). The maximum charging/discharging power limitations of the EES are formulated in (22) and (23), respectively. The binary variable of these equations is used to avoid simultaneous EES's charging and discharging. The lower and upper limitations of the energy to be stored in the EES are described in (24). The stored energy behavior of the EESs is formulated as (25)-(27). The energy limitation of the ESS to provide reserve is modeled in (28). Also, the power limitation of the EES to provide the reserve capacity is modeled in (29). As shown in this equation, increasing the charging power of the EES increases its capability to provide the reserve capacity.

$$p_{s.t}^{EES\_ch} \leq \overline{P}^{EES\_ch} B_{s.t}^{EES} \quad (22)$$

$$p_{s.t}^{EES\_dch} \leq \overline{P}^{EES\_dch}\left(1 - B_{s.t}^{EES}\right) \quad (23)$$

$$\underline{E}^{EES} \leq E_{s.t}^{EES} \leq \overline{E}^{EES} \quad (24)$$

$$E_{s.t}^{EES} = E_{s.t-1}^{EES} + \left[\left(p_{s.t}^{EES\_ch}\eta^{EES\_ch}\right) - \left(p_{s.t}^{EES\_dch}/\eta^{EES\_dch}\right)\right] \quad (25)$$

$$E_{s.t}^{EES} = E^{EES.ini} + \left[\left(p_{s.t}^{EES\_ch}\eta^{EES\_ch}\right) - \left(p_{s.t}^{EES\_dch}/\eta^{EES\_dch}\right)\right] \quad (26)$$

$$E_{t=24}^{EES} = E^{EES.ini} \quad (27)$$

$$p_t^{EES\_R}/\eta_t^{EES\_dch} \leq E_{s.t}^{EES} - \underline{E}^{EES} \quad (28)$$

$$\left(p_t^{EES\_R} - p_{s.t}^{EES\_ch} + p_{s.t}^{EES\_dch}\right) \leq \overline{P}^{EES\_ch} \quad (29)$$

- **TES's constraints**

The TES's technical constraints are described in (30)-(35). The same approach for the EES is used to model the constraints of the TES.

$$p_{s.t}^{TES\_ch} \leq \overline{P}^{TES\_ch} B_{s.t}^{TES} \quad (30)$$

$$p_{s.t}^{TES\_dch} \leq \overline{P}^{TES\_dch}\left(1 - B_{s.t}^{TES}\right) \quad (31)$$

$$\underline{E}^{TES} \leq E_{s.t}^{TES} \leq \overline{E}^{TES} \quad (32)$$

$$E_{s.t}^{TES} = E_{s.t-1}^{TES} + \left[\left(p_{s.t}^{TES\_ch}\eta^{TES\_ch}\right) - \left(p_{s.t}^{TES\_dch}/\eta^{TES\_dch}\right)\right] \quad (33)$$

$$E_{s.t}^{TES} = E^{TES.ini} + \left[\left(p_{s.t}^{TES\_ch}\eta^{TES\_ch}\right) - \left(p_{s.t}^{TES\_dch}/\eta^{TES\_dch}\right)\right] \quad (34)$$

$$E_{t=24}^{TES} = E^{TES.ini} \quad (35)$$

- **IL's constraints**

The amount of the curtailed load to provide energy and reserve is limited to the maximum capacity of load curtailment (Eq. (36)).

$$p_t^{IL} + p_t^{IL\_R} \leq \overline{P}^{IL}.p_t^{IL}.p_t^{IL\_R} \geq 0 \tag{36}$$

3.3. Robust two-stage stochastic problem

To consider the effect of the uncertainty of the RT energy market price on the MGO's decisions, the obtained two-stage stochastic framework in the previous sub-section is reformulated as a robust optimization problem. The aim of the robust model is to minimize the objective function (*RETC*) considering the robust (Eqs. (38) and (39)) and the MG's resources (Eqs. (13)-(36)) constraints. The objective function of the robust method is equal to the sum of the *ETC* and a new term which in turn consists of the uncertain parameter and its related decision variable. In this term, an interval is considered (between λ_{-t}^{RT} and $\overline{\lambda}_t^{RT}$) for the RT energy price as the uncertain parameter. The variable ξ_t is multiplied in this maximization term to describe the robustness of the model. Sum of this variable in the operation time period is lower than or equal to the robustness parameter Γ as modeled in (38). To replace the maximization term with some constraints, the dual variables of Z and q_t are defined for Eqs. (38) and (39), respectively. Although the variable (ξ_t) is modeled as a continuous one (Eq. (39)) to avoid the non-convexity of the model, it acts as a binary variable as described in [27].

$$RETC = ETC + Max\frac{\left(\overline{\lambda}_t^{RT} - \lambda_{-t}^{RT}\right)}{2}p_t^{MG\_R}k\xi_t \tag{37}$$

s.t.
Eqs. (13)-(37),

$$\sum_t \xi_t \leq \Gamma : Z \tag{38}$$

$$0 \leq \xi_t \leq 1 : q_t \tag{39}$$

The dual form of the maximization model is obtained as follows:

$$Min\sum_t q_t + \Gamma Z \tag{40}$$

$$q_t + \Gamma Z \geq \frac{\left(\overline{\lambda}_t^{RT} - \lambda_{-t}^{RT}\right)}{2}p_t^{MG\_R}k \tag{41}$$

$$q_t \geq 0.Z \geq 0 \tag{42}$$

Replacing the dual problem in (37), the final model is obtained as follows:

$$RETC = ETC + \sum_t q_t + \Gamma Z \tag{43}$$

s.t.
Eqs. (13)-(37),

$$q_t + \Gamma Z \geq \frac{\left(\overline{\lambda}_t^{RT} - \lambda_{-t}^{RT}\right)}{2}ky \tag{44}$$

$$-y \leq p_t^{MG\_R} \leq y \tag{45}$$

$$q_t \geq 0.Z \geq 0.y \geq 0 \tag{46}$$

The proposed robust two-stage stochastic model is solved in GAMS 24.1.2 software environment using the CPLEX solver.

3.4. Limitations of the proposed model

In the proposed model of this study, the failure rate of the MG's resources, which may lead to not delivering the reserve capacity in the real operation, is not modeled. The proposed two-stage stochastic model can only be used to model the uncertain parameters with known PDFs.

4. Numerical results

In this section, the optimal decisions of the MGO to contribute to the DA markets of energy and reserve besides supplying its local electrical and thermal energy demands are investigated. For this aim, the proposed robust two-stage stochastic model is applied on a MG. The required input data to obtain the numerical results is given in the first sub-section. Then, the results are presented, and the sensitivity of the reserve capacity provided by the MGO and its ETC to the robust parameter are displayed.

4.1. Input data

The MG consists of a CHP unit, the PV arrays, an EES, and a TES. The characteristics of the CHP unit with 400 kW capacity are given in Table 1 [28]. The PV arrays have the maximum power of 60 kW and the ESS and the TSS have capacities of 400 kWh. Fig. 3 proposes the electrical and the thermal demands [29]. The generated power of the PV system proposed in [30] is modified to be used in this case study as shown in Fig. 4. The natural gas price is shown in Fig. 5 [31]. Tables 2 and 3 show the ESS, TSS and PV features, respectively [32]. The load interruption cost is given in Fig. 6 [17]. The proposed energy and reserve market prices are considered in this paper are shown in Fig. 7 [33].

4.2. Modeling uncertainties

The normal and the Weibull PDFs are used to create the uncertain behavior of the demand and the generated power of the PVs, respectively. Details of the parameters of these PDFs are described in [34]. The normal and the Weibull PDFs are divided into seven and five intervals and the upper and the lower bounds of these intervals are determined regarding the mean value of these PDFs. The forecasted values of the demand and the output power of the PV system are assumed as the mean value of their PDFs. Then, regarding the probability of each interval, a large number of samples (24000 samples) are generated. Then, the scenario tree method is employed to generate the scenarios. In this method, the time period of the problem is considered as the stages and the produced samples are defined as the nodes. Then, a scenario is defined as a leaf which connects the nodes to each other. For example, for a problem with the time period being 3 and having 10 produced samples, a scenario tree is obtained as Fig. 8. As shown in this figure, there are 6 leaves where the first leaf connects nodes 1, 2, and 5 and the last leaf connects nodes 1, 4, and 10. The stages and the nodes of the proposed scenario tree in this paper are 24 and 24000, respectively, regarding which 1000 leaves (scenarios) are generated. Since the large number of the scenarios increase the complexity of the model (number of equations and variables), the reduction method proposed in [35–37] is used to reduce the scenarios. For this purpose, the produced 1000 scenarios are reduced to 15 using the fast-forward method which is introduced as the best algorithm from the viewpoint of accuracy [38].

Table 1
Characteristics of the CHP.

Parameters	Value	Unit
$\overline{P}^{CHP}$	400	kW
η^{CHP_E}	0.4	–
η^{CHP_T}	0.45	–
β	0.0924	m^3/kWh

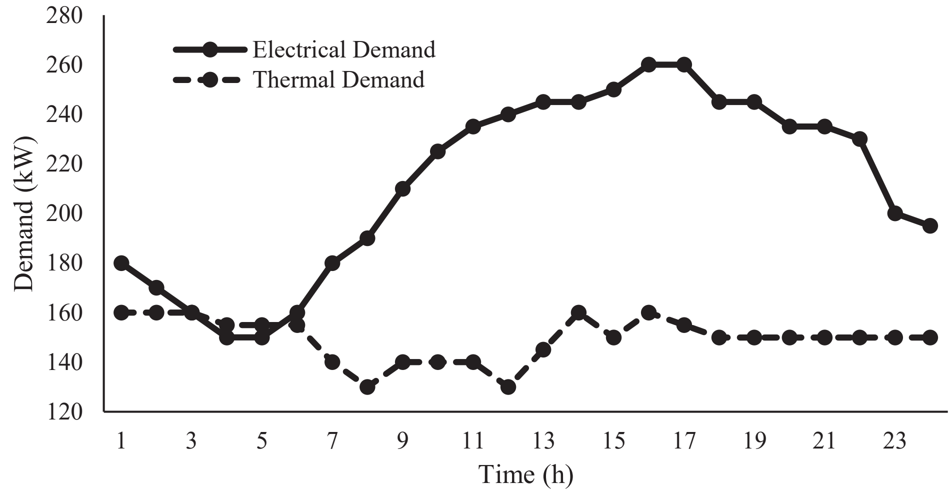

Fig. 3. Load consumption profile.

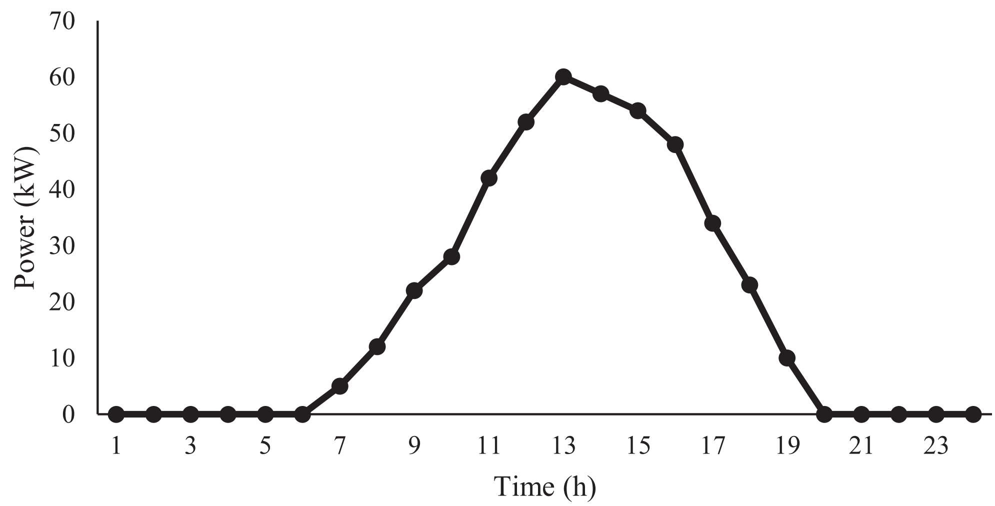

Fig. 4. Output power of PV system.

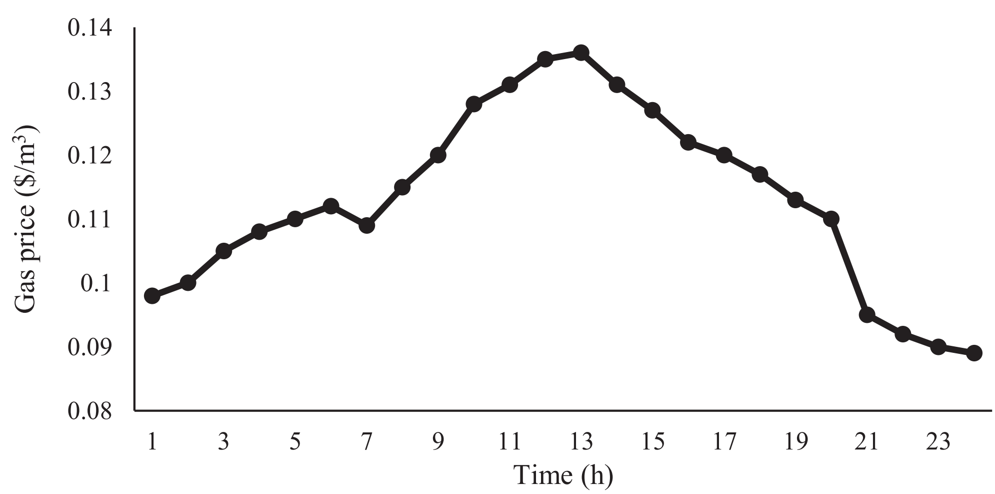

Fig. 5. Natural gas price.

Table 2
Characteristics of the EES and TES.

Parameters	Value	Unit
$\overline{P}^{EES\backslash\_ch}/\overline{P}^{TES\backslash\_ch}$	120	kW
$\overline{P}^{EES\backslash\_dch}/\overline{P}^{TES\backslash\_dch}$	120	kW
$\underline{E}^{EES}/\underline{E}^{TES}$	100	kWh
$\overline{E}^{EES}/\overline{E}^{TES}$	400	kWh
$E^{EES,ini}/E^{TES,ini}$	100	kWh
$\lambda^{EES}/\lambda^{TES}$	0.001	$/kWh
$\eta^{EES\backslash\_ch}/\eta^{EES\backslash\_dch}$	0.95	–
$\eta^{TES\backslash\_ch}/\eta^{TES\backslash\_dch}$	0.95	–

Table 3
Characteristics of PV and the main grid.

Parameters	Value	Unit
$\overline{P}^{grid}$	200	kW
η^{grid}	0.99	–
λ^{PV}	0.001	$/kWh

This reduction method is employed through the General Algebraic Modeling System/Scenario Reduction (GAMS/SCENRED) package. Details of using this package to reduce the scenarios are described in [37]. The occurrence probability of the generated scenarios is shown in Table 4.

4.3. Results

The cost/revenue terms obtained from solving the optimization problem of the MGO are shown in Tables 5 and 6. The minus sign obtained for the ETC in Table 5 shows that the MGO earns profit from participating in the energy and the reserve markets. This is while, when the MGO only participates in the energy market, its ETC is 179.87 $. Therefore, participating in the reserve market decreases the ETC of the MGO from 179.87 $ to −31.57 $. As shown in Table 5, the main reason of this reduction is the high revenue obtained by the MGO from participating in the reserve market, i.e. 253.22 $. Also, the total cost of the MGO corresponding to the second-stage decisions in each scenario is shown in Table 6.

The MGO's results consisting of the electrical and thermal energy

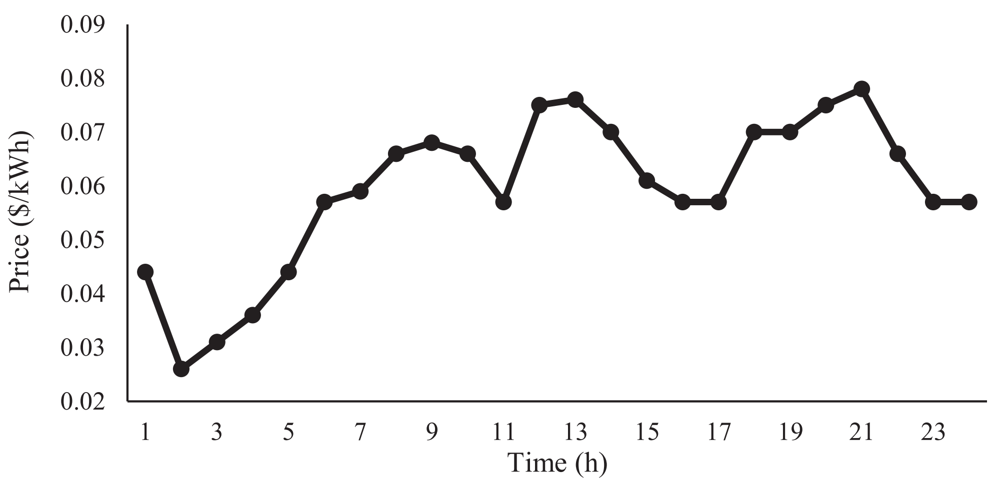

Fig. 6. IL's price.

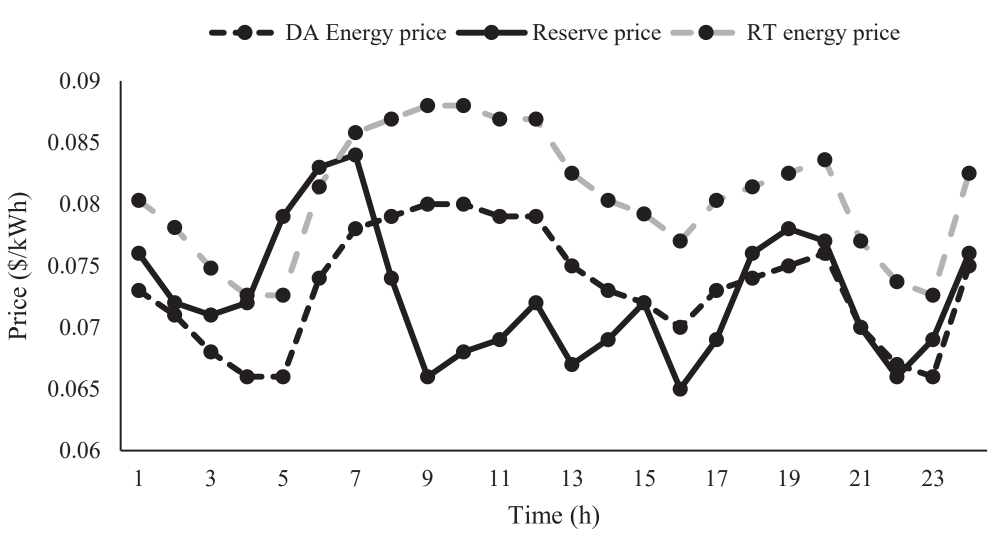

Fig. 7. Forecasted energy and reserve market prices.

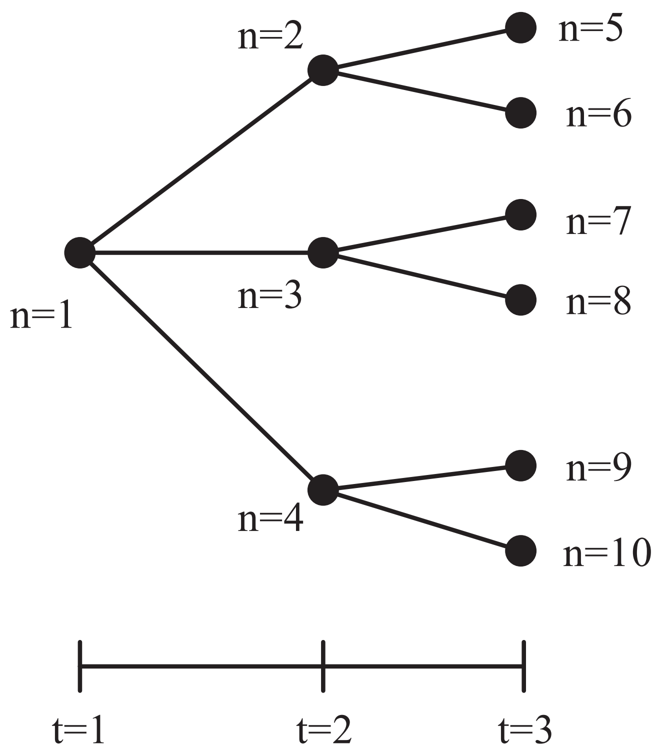

Fig. 8. An example of the scenario tree method with 3 stages and 10 nodes.

Table 4
Probability of occurrence of scenarios in two-stage stochastic model.

Scenario #	Probability of occurrence	Scenario #	Probability of occurrence
1	0.061	9	0.065
2	0.049	10	0.064
3	0.047	11	0.074
4	0.091	12	0.087
5	0.051	13	0.067
6	0.085	14	0.063
7	0.077	15	0.054
8	0.065		

Table 5
ETC and cost/revenue related to the first-stage decisions.

Cost/Revenue	Value ($)
ETC	−31.57
TC^{FD}	−115.64
C^{E}	112.25
C^{IL_E}	0
C^{IL_R}	24.38
C^{EES_R}	0.95
R^{R}	253.22

balances and its decisions to provide the reserve capacity for the market for the first scenario are shown in Figs. 9–11, respectively.

As shown in Figs. 9 and 10, the CHP unit is scheduled to produce high electrical power in hours 1 and 2 in comparison with hours 3 and 4 regarding the low natural gas price in hours 1 and 2. With this decision, the MGO meets its demand and it charges the EES. In hours 3 and 4, regarding the high natural gas price in comparison with the previous hours, the MGO decreases the power generation of the CHP unit on one hand, and it discharges the EES to supply the electrical demand and to sell electricity to the market on the other hand.

Table 6
Total cost of the second-stage decisions in each scenario.

Scenario #	Cost ($)	Scenario #	Cost ($)
1	83.21	9	85.95
2	84.64	10	83.44
3	83.19	11	82.95
4	83.66	12	85.12
5	83.93	13	82.35
6	82.96	14	84.37
7	82.84	15	82.90
8	87.38		

The MGO charges the EES in hours 5–7 with purchasing energy from the market because of the low price of energy market in these hours. Then, the MGO discharges the EES to meet its demand in hours 8–10 and to sell energy to the market with a high energy market price in hours 8 and 9. The other reason for this decision of the MGO is the high reserve price in hours 5–7 and the low reserve price in hours 8 and 9. When the EES is charged in hours 5–7, its capacity to provide the reserve capacity increases as shown in Fig. 11. On the other hand, when the MGO discharges the EES in hours 8 and 9, its capacity to provide the reserve capacity for the market decreases as shown in Fig. 11.

Since the natural gas price in hours 12 and 13 is high and the demand increases in these hours in comparison with 11, the MG discharges the EES in hours 12 and 13 to supply its demand instead of producing more power from the CHP unit. For this purpose, the EES is charged in hour 11 with purchasing energy from the market. The MG purchases energy from the DA market in hours 14–16 to charge its EES so that it can discharge the EES in hours 17–20 with high DA energy market price to meet its demand as shown in Fig. 8. Hence, the MGO sells energy to the DA market in hour 17 besides supplying the demand. Charging the EES in hours 14–16 increases the EES's capacity to provide more reserve for the MGO as shown in Fig. 11.

Since the reserve market price in hour 21 is more than 22, the MGO decides to charge the EES with purchasing energy from the market in hour 21. This decision of the MGO increases the capability of the EES to provide more reserve in hour 21. In hour 22, with discharging the EES, the MGO meets its electrical demand, and it exports any extra power to the market as shown in Fig. 8. Because of the lower energy market price in hour 23 (less than 24), the MGO purchases energy from the market to charge the EES in hour 23 and then it discharges the EES in hour 24 to supply the demand.

As shown in Fig. 10, the decisions of the MGO to charge and discharge the TES depend on its decisions to dispatch the CHP unit to meet the electrical energy balance. When the MGO decides to dispatch the CHP to provide more electrical energy in hours 1–3, 7–10, 12, 13, and 17–20, the CHP capacity to provide the thermal energy also increases with a subsequent charging of the TES.

Then, in the hours that the MGO decides to purchase more energy from the market, the CHP electrical output power decreases and the thermal output energy decreases consequently. Therefore, the MGO discharges the TES in hours 5, 11, 15, 16, and 21 to supply the thermal energy demand.

The reserve provided by the MGO to the market is met by the IL and the EES as shown in Fig. 11. Since the price of providing the reserve capacity to the MG by the IL is lower than the reserve price market, the IL is asked to employ its whole capacity to provide reserve as shown in Fig. 11. As shown in this figure, most of the reserve capacity provided by the MGO to the market is supplied by the EESs. When the MGO decides to charge the EESs in hours 1, 2, 5–7, 11, 14–16, 21, and 23, its capacity to provide the reserve for the MGO increases as shown in Fig. 11. On the other hand, when the EESs are discharged with the aim of supplying the electrical demand of the MG, its capacity to provide the reserve decreases in hours 3, 4, 8–10, 12, 13, 17–20, 22, and 24 as shown in Fig. 11. This behavior of the EES confirms its technical constraint which is modeled in (29). This constraint declares that charging the EES

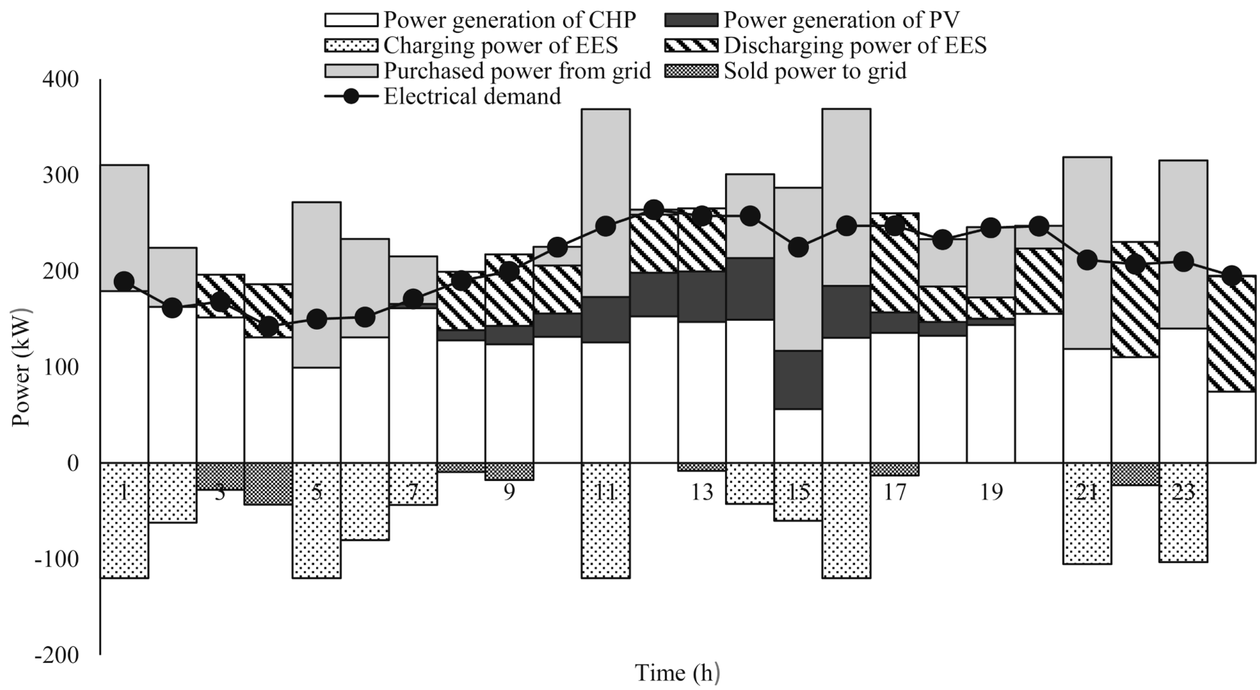

Fig. 9. Electrical energy balance in the MG.

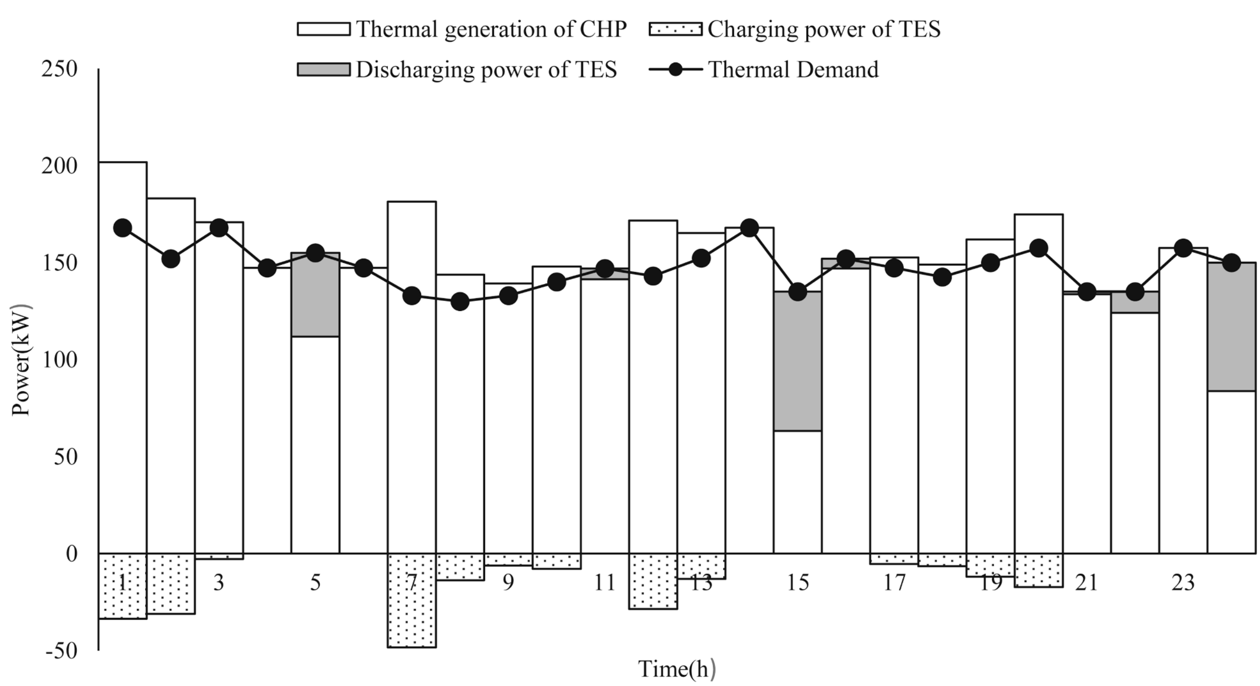

Fig. 10. Thermal energy balance in the MG.

increases its capacity to provide the reserve capacity while discharging that would cause a decrease in the reserve capacity.

To investigate the sensitivity of the MGO's decisions to the robust parameter, this parameter changes from $\Gamma = 0$ (without considering the uncertain parameter) to $\Gamma = 10$ (with the most degree of considering the uncertain parameter in this paper). The uncertain parameter of this case is the RT energy price. The uncertainty interval of this parameter is between 0.85 and 1.15 of its forecasted value. When the robust parameter increases, the risk-averse MGO decides to decrease its provided reserve for the market so that the ETC of the MGO increases (the minus ETC decreases) as shown in Fig. 12.

4.4. Comparing the proposed method with conventional methods

In this paper, the uncertainties of the demand and the output power of the PV system are modeled using the two-stage stochastic model. There are two conventional models in facing the uncertainties of the demand and the PV output power in such problems: 1) the deterministic method and 2) the probabilistic method. In the deterministic model, the uncertainties of the demand and the output power of the PV system are not considered and it is assumed that these parameters are forecasted with no errors. In the probabilistic method, the expected values are determined for all decision variables such as power trading with the

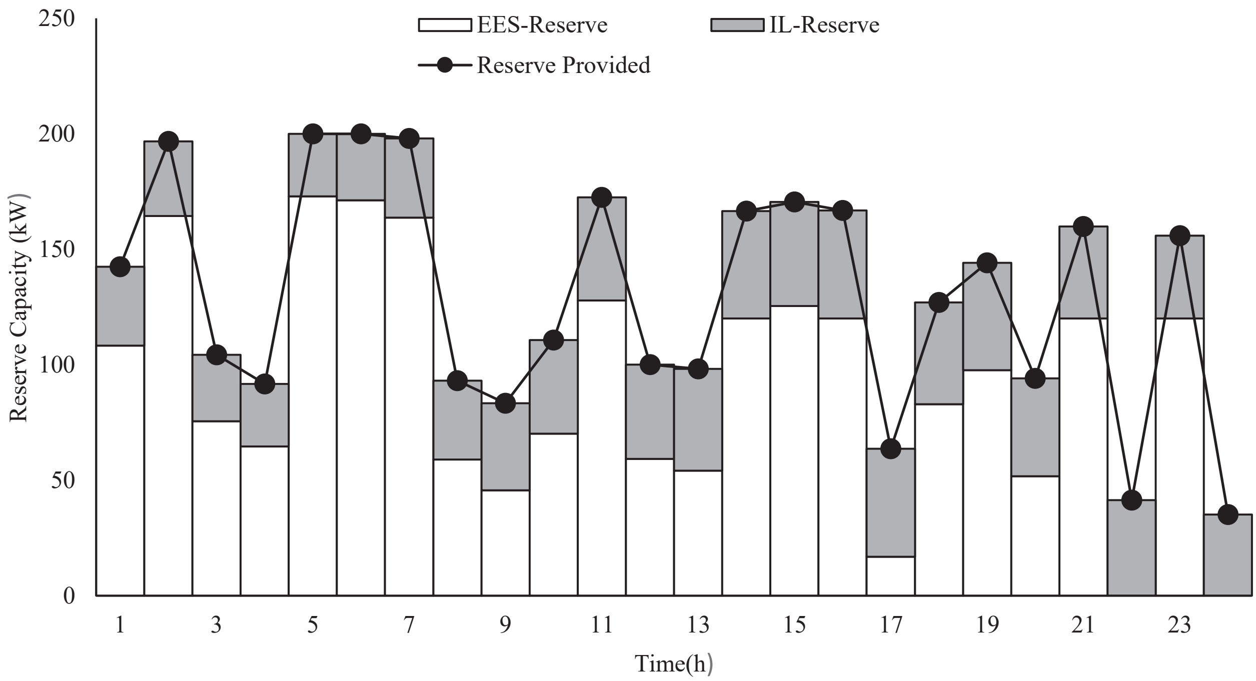

Fig. 11. The reserve capacity balance of the MG.

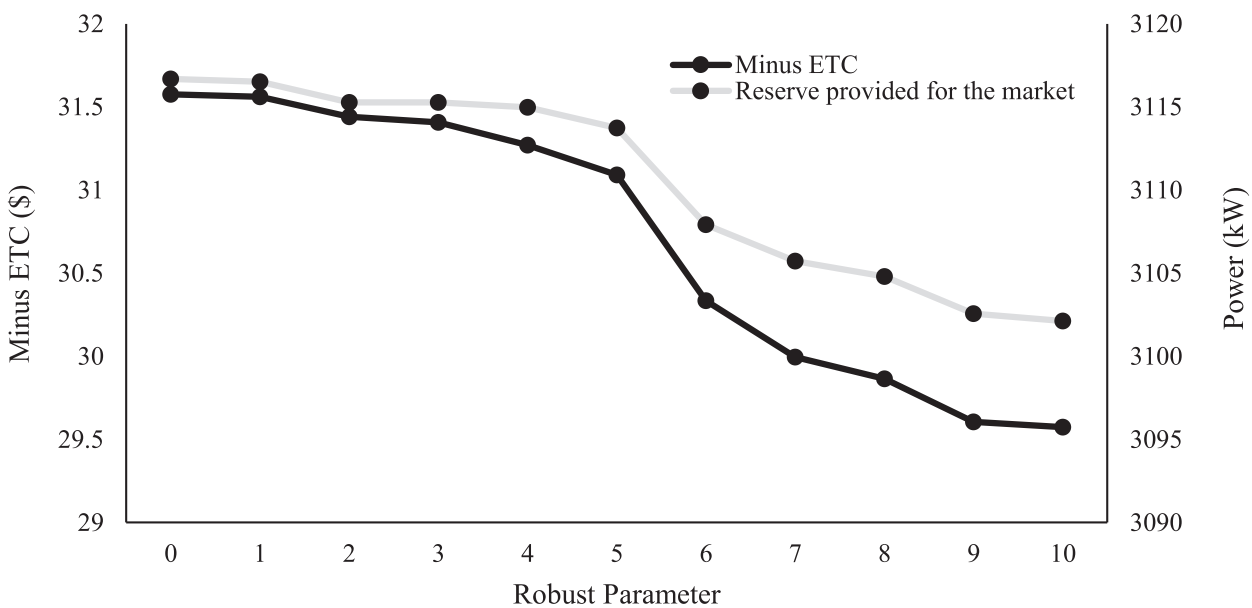

Fig. 12. The sensitivity of the reserve provided for the market and the ETC to the robust parameter.

energy market and the reserve capacity provided for the market. The results of the proposed two-stage stochastic model in this paper are compared with the deterministic and the probabilistic methods in Table 7. In all methods, i.e. the proposed two-stage stochastic model in this paper and the deterministic and the probabilistic methods, the uncertainty of the RT energy market price is modeled through the robust model. The variations of the MGO's bids in the DA markets regarding the robust parameters in all methods are compared in Table 7. As shown in this table, in all methods the net power trading[1] of the MGO with the market and the amount of the reserve provided for the market decrease in the worst case in comparison with the base case. However, the amount of reduction in the two-stage stochastic method is lower than the other methods. In fact, with stochastic scheduling of the MG's resources, i.e., CHP, TES, and EESs, the reliable MGO's decisions in the DA markets are obtained so that increasing the robust parameter, these decisions would face the least reduction in comparison with the other methods.

4.5. Sensitivity of the results to the number of scenarios

To prove the accuracy of the proposed scenario reduction method, the effect of increasing the number of scenarios on the results and the

[1] Defined as the purchased power from the market minus the power sold to the market.

Table 7
Sensitivity of the market decisions to the robust parameters in deterministic, probabilistic, and two-stage stochastic methods.

	Net power trading with the DA market			Reserve provided for the DA market		
	Deterministic	Probabilistic	Two-stage stochastic	Deterministic	Probabilistic	Two-stage stochastic
Base case, $\Gamma = 0$ (p.u.)	1	1	1	1	1	1
Worst case, $\Gamma = 10$ (p.u.)	0.982	0.984	0.992	0.993	0.993	0.996
The amount of reduction (%)	1.8	1.56	0.8	0.7	0.7	0.4

Table 8
Sensitivity of the results and the model statistics to the number of scenarios.

Number of scenarios	ETC (p.u.)	Reduction of the ETC in the worst case (%)	Model statistics		
			Single equations	Single variables	Discrete variables
15	1	6.33	10,419	7015	744
20	0.992	6.34	13,756	9257	984
25	0.997	6.36	17,071	11,477	1224
30	0.998	6.34	20,386	13,697	1464
35	0.999	6.34	23,701	15,917	1704

model statistics is shown in Table 8. The results presented in this table show that increasing the number of the scenarios changes the variation of the ETC of the MGO slightly. It should be noted that the MGO's ETC in the case with 15 scenarios is considered as 1p.u. The change of the reduction of the ETC in the worst case ($\Gamma = 10$) with increasing the number of scenarios is also so slight as shown in Table 8. This is while, with increasing the number of the scenarios, the number of equations and the decision variables of the model increase.

5. Conclusion

In this paper, the MGO's bids in the DA markets of energy and reserve are optimized considering the stochastic decisions to supply the local electrical and thermal energy demands. For this aim, a robust two-stage stochastic optimization framework is developed to consider the uncertainties of the electrical demand, the power generation of the PV system, and the RT energy price. In this model, the MGO's first-stage decisions, i.e., its bids in the markets and the schedules of the IL are determined considering the optimal dispatching of the EES, TES, and CHP as the scenario-based decisions. Also, the proposed robust model leads to the MGO's ETC which is robust against the uncertainty of the RT energy market price in the worst case. The main conclusions from the results are as follows:

The results showed that the MGO is obtaining a major profit from participating in the reserve market. For this purpose, the MGO's decisions in the markets highly depend on the optimal dispatching of the EES. The MGO charges the EES in the hours with low energy price and high reserve price to provide more reserve capacity for the reserve market in the same hours. Then, the MGO discharges the EES to sell energy to the market in the other hours with high energy prices. These decisions of the MGO to trade energy with the market and to dispatch the EES have major effects on the output electrical and thermal energy of the CHP which leads to optimal dispatching of the TES by the MGO.

Modeling the uncertainties of the demand and the output power of the PV system leads to obtaining more robust objective function in the worst case in comparison with the deterministic and probabilistic approaches. In fact, in the two-stage stochastic model, the amount of the changes of the MGO's decisions in the markets is lower than the deterministic and probabilistic methods when the MGO faces the worst case.

The sensitivity of the MGO's decisions to the robust parameter showed that increasing the robust parameter decreases the provided reserve for the market regarding which the ETC increases.

CRediT authorship contribution statement

Salah Bahramara: Conceptualization, Methodology, Formal analysis, Writing – review & editing, Writing – original draft. **Saman Shahrokhi:** Investigation, Methodology, Software, Data curation, Writing – original draft. **Pouria Sheikhahmadi:** Investigation, Methodology, Software, Data curation, Writing – original draft. **Rahmat Khezri:** Formal analysis, Writing – review & editing, Validation. **S.M Muyeen:** 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.

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