Day-Ahead Optimal Bidding of Microgrids considering Uncertainties of Price and Renewable Energy Resources

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Abstract

Unpredictable faults always reduce the stability and reliability of the electrical system. The increasing use of renewable energy sources (RES) in recent decades has exacerbated power system problems. Microgrids (MG) participation in Ancillary Services (AS) market is a suitable solution for the optimal performance of power systems in these conditions. MGs can also maximize their profits by participating in the AS market. In this paper, the optimal stochastic bidding strategy in joint energy and AS (regulation up and regulation down, spinning reserve and non-spinning reserve) market is modeled. Uncertainty of wind speed and solar radiation is modeled using Weibull and Beta probability distribution function (PDF) and probability of call AS is computed for all available AS. Therefore, the risk of the bidding strategy is controlled using conditional value at risk (CVaR). ERCOT market simulation has been carried out in order to determine the participation of each generator in all of the mentioned markets for different prices of energy and also to present the bidding curve, based on real-world data.

***Keywords*:** Ancillary services; Optimal bidding; Regulation; Spinning reserve; Non-spinning reserve.

Nomenclatures

Acronyms

CVaR	Conditional Value at Risk
DER	Distributed energy resources
DG	Distributed generation
EM	Energy market
AS	Ancillary services
GT	Gas turbine

ESS	Energy storage system
MG	Microgrid
PV	Photovoltaic system
RES	Renewable energy sources
WT	Wind turbine
PDF	Probability distribution function

Indices

req	Index of requirement
ch	Index of charge storage
dch	Index of discharge storage
s	Index of scenario
n	Index of set of generating units
e	Index of energy market
rd	Index of regulation down
ru	Index of regulation up
sp	Index of spinning reserve
ns	Index of non-spinning reserve
as	Index of ancillary services
asg	Index of ancillary services generation
ave	Index of average
std	Index of standard

Variables

R	Revenue
P	Price
OP	Offer price
E	Energy
C	Cost function
var	Value at risk
η_s	Auxiliary variable for calculating CVaR
$E_{st}^{sh/dsh}$	Charging/discharging power of storage
$s_{sh/dsh}$	Charging/ discharging state of storage

Parameter

μ	Average of Beta distribution
σ	Standard deviation of Beta distribution
E_{pvr}	Standard power generation of PV
$E_{st}^{dsh\ max}$	Maximum discharge in one hour
$E_{st}^{sh\ max}$	Maximum charge in one hour
λ	Probability of call AS
p_{wr}	Standard power generation of WT
r	Solar radiation
V	Wind speed
v_{in}	Cut-in wind speed
v_r	Rated wind speed
v_{out}	Run-out wind speed
$\pi(s)$	Probability of each scenario
δ	Confidence level
W	Risk-aversion parameter
UR	Ramp up rate
DR	Ramp down rate
E^{max}	Maximum generation power
E^{min}	Minimum generation power
ζ^{st}	Discharging efficiency
η^{st}	Charging efficiency
a	Annuitization coefficient (dimensionless)
I	Investment costs, per unit installed power ($/MW)
G	Operating & maintenance costs, per unit generated energy ($/kW)
γ	interest rate
N	Investment lifetime

1. Introduction

1.1 Background

In recent years, because of different reasons (fossil fuel pollution, transmission line losses because of the thermal power plants distance from consumers, government taxes, demand of global communities due to stop using fossil fuels, …) development of renewable energy sources (RES) has seen a significant boost. Today, RES such as the Photovoltaic systems (PV) and Wind turbines (WT) are an integral part of the electrical grid [1,2].

On the other hand, using renewable energy is generally increasing variability and uncertainty of power system [3]. Adding these problems to power system's possible problems (loss of transmission lines, unintended failure of centralized power plants, etc.) makes the power system unstable and reduces its reliability. Provision Ancillary Service (AS) using distributed generation (DG) and energy storage systems (ESS) in a microgrid (MG) can be a solution to these problems.

MGs consist of renewable energy power plants, fossil fuel power plants, ESS and electrical loads. From a market point of view, a MG is a controllable consumer or producer. Generally, MGs main applications are on residential level (hospitals, sport centers, hotels) [2,4,5]. The main income of MGs is from the sale of electrical energy. Also, MGs can increase their profitability by participating in the AS markets [6]. AS are operational services provided by the transmission system operator to maintain a balance between supply and demand, system security and reliability and provide appropriate quality of electrical energy. These AS are generally offered in competitive economic markets [7].

By using renewable energies, grids need more AS than before because of increasing uncertainties of RES [8]. This paper discusses regulation up and regulation down, spinning reserve and non-spinning reserve AS. MGs can balance energy with less losses than centralized generators, because MGs distance from the consumer are less than concentrated power plants.

Since the production volume of MGs mentioned in this paper is small and they also follow the market price (price taker) and their bid price has no significant effect on the market, they can have the most appropriate offer for simultaneous participation in the energy market (EM) and AS markets to achieve the highest possible profitability with optimal planning by pay attention to all possible conditions (uncertainty of wind and solar generators production, uncertainty of prices ,etc).

1.2. Literature review

Many articles discussed AS, technical and financial points related to them. Then, studies have examined the profit maximization of MGs with simultaneous participation in the energy and AS market. At first, most of the papers examined their proposed models with predicted and determined values (for energy and AS prices, production of renewable generators, etc.). Supplementary studies paid more attention to uncertainties (energy and AS price, wind and solar production).

In [2], multi-stage stochastic programming model used for optimal planning of virtual power plants (VPP) in day-ahead energy and secondary reserve markets considering uncertainties of wind speed and clearing price.

Report [3] describes different types of AS (intra-hour and inter-hour) and related constraints in detail. Authors of this reference developed MG optimal scheduling model for coordination between production and consumption and participation in the AS market. A proposed model for a 24-hour planning is presented for scheduling 1-minute frequency regulation service, 10-minute load following service and hourly ramping service. In [4], the strategy of economic power supply in the DAM with respect to energy prices and considering the uncertainty of renewable power production (solar energy), due to the risk management is expressed. In addition, in this study, the participation of thermal power plants in heat supply is also mentioned.

In [8], hybrid stochastic/robust optimization model is developed for optimal bidding strategy considering flexible ramping products, uncertainties of renewable generation and market prices and participation of different DER (WTs, PVs, MTs and ESS) in day-ahead energy, reserve and regulation markets. In [9], an equilibrium bi-level model is proposed to find the best MG planning of buy or sell energy in day-ahead market (DAM). Authors of [10] presented a novel nonlinear stochastic method for the production in regulation up and down market by a high number of PVs and ESS. The authors of this reference state that is more convenient for PVs to participate in regulation up.

In [11], an arbitrage model for simultaneous participation in the active power, reactive power and reserve markets for VPPs is modeled according to the constraints of the system to maximize VPPs profits by considering the capacitor bank. Authors of [12] developed the bidding strategy of MGs simultaneous auctions in integrated energy and AS markets under uncertainties. The output decisions of this formulation are the estimated total cost and the amount of participation in AS markets. Solar radiation, probability of calling AS, market prices and load demand uncertainties modeled using their PDFs.

In [13], spot and balancing market is modeled via mixed-integer nonlinear program to reduce weekly production costs. The hourly price of energy and AS is also predicted in this reference and has presented that by using this method the cost will be reduced up to 20%. Study [14] suggests an MINLP bidding strategy model to maximize MGs profit in joint energy and reserve market with using CVaR risk management. Authors of this reference considered uncertainties of solar radiation, wind speed, outage of DER, load and penalty costs for wrong estimation of productions. In [15], a comprehensive MINLP model proposed the optimal offering of a low voltage MG in the day-ahead joint energy and AS markets with considering the uncertainties of renewable power production (solar and wind energy). Authors of this reference generate scenarios of market prices using lognormal PDF.

Reference [16] presented the operation strategy of the PVs and ESS for participate in the coupled energy and AS market in order to maximize the profitability considering solar production forecast and hourly energy prices. In [17], a stochastic three-stage bidding strategy for maximizes generators (WT, gas turbine (GT), ESS) expected profit and the lowest amount of emission in joint energy and AS market is proposed. Authors of this reference discussed spinning reserve market profit is more than the EM for the ESS. Ref. [18] described optimal planning for the simultaneous participation of the MG in the energy and AS market as well as the supply of thermal consumers. This model shows that the level of participation in each of the markets is related to the price of energy and risk management.

Authors of [19] presented a method for using ESS as AS resources, especially as a spinning reserve. The various scenarios that are compared to the reference scenario are generated by considering forecast uncertainties of load and renewable output. In [20] a comprehensive optimal bidding strategy model has been developed for renewable MGs to take part in day-ahead (energy and reserve) and real-time markets. They considered uncertainties of wind speed, solar irradiance, and load realizations via Weibull, Beta, and normal probability density functions, respectively. Furthermore, the risk of participation in the markets has been investigated by the use of CVaR

1.3. Contributions

Table 1 describes the contribution of the paper over the existing literature. Although many reports have presented optimal planning for the simultaneous participation of the MG in the energy and AS market in the literature, the exact operating cost of DER is not considering in the objective functions and the relation between participation spinning reserve and non-spinning reserve has not been addressed yet. Also, not much information about probability of call AS is available in previous studies; this paper describes the probability of call AS for all available AS.

The contribution of the paper can be summarized as below:

- Proposing a new model for calculating the operating cost of the MG in different modes of participation in different markets;
- Simultaneous participation in the EM and AS markets including regulation up and regulation down, spinning reserve and non-spinning reserve. To the best of the authors' knowledge, it is the first time that the relation between participation in spinning reserve and non-spinning reserve is modeled for the MG operation;
- Employing the probability of call for all available AS that has not been reported in the literature.

Table 1. Taxonomy of recent works

Reference	Wind speed modelling method	Solar radiation modelling method	Variation modelling method	AS			Separation regulation up and regulation down	Energy storage	Probability of call AS	Risk modelling method
				Regulation	Spinning reserve	Non-spinning reserve				
2				■			■	■		
3				■	■	■		■		
4		Analog Ensemble	Analog Ensemble							
6					■			■		
8	Stochastic/Robust	Stochastic/Robust	Stochastic/Robust		■			■		Stochastic/Robust
10				■			■	■		Stochastic
11					■			■		
12	IGDT	IGDT	IGDT					■	■	CVaR and IGDT
13			Stochastic	■						Stochastic
14	Weibull PDF	Lognormal PDF	Tent mapping		■			■		CVaR
15			Lognormal pdf		■			■		
17	Stochastic		Stochastic		■			■		
18					■			■		
19	Scenario generation	Scenario generation			■			■		Scenario generation
20	Weibull PDF	Beta PDF			■			■		Stochastic/CVaR
This paper	Weibull PDF	Beta PDF	Sensitivity analysis	■	■	■	■	■	■	Stochastic/CVaR

1.4. Paper organization

The rest of the paper is organized as follows: Section 2 describes the problem, introduces different types of AS, models objective function, describes all constraints and uncertainties and risk management. Section 3 is numerical result for real-world data, and finally section 4 is the conclusion.

2. Problem description and Mathematical modeling

2.1. Market modeling

With proper planning, MGs can participate simultaneously in energy and AS markets with the least amount of risk to maximize their profits. MGs generally include RES, so special attention should be paid to the uncertainties of these generators in planning. This paper discusses regulation up and regulation down, spinning reserve and non-spinning reserve AS.

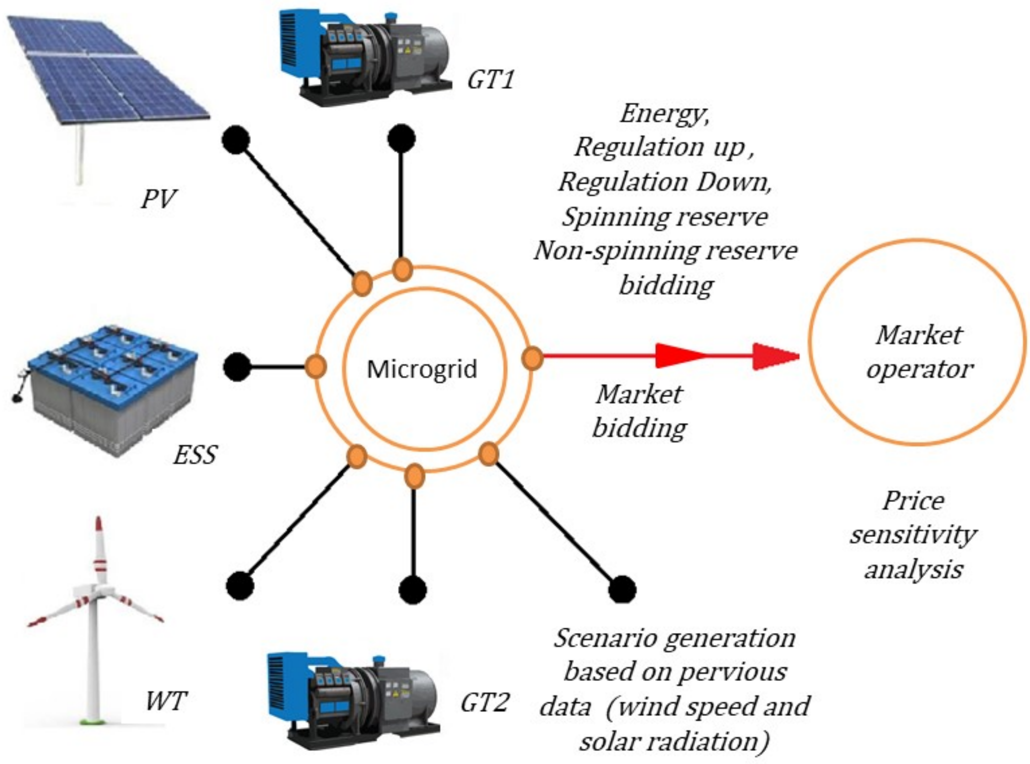

Fig. 1. MG test system

2.2. Ancillary services

AS are operational services provided by the transmission system operator to maintain a balance between supply and demand, system security and reliability and provide appropriate quality of electrical energy. These AS are generally offered in competitive economic markets [7, 21].

2.2.1. Regulation

Frequency control is used to cover small fluctuations between supply and demand. To control the frequency, generators must be able to change their output in a very short period of time (usually within a few seconds). High-frequency deviation can cause the generators to shut down and fault in protection relays. Frequency control is done by changing the active output power of power plants. [22]. Some markets offer only one frequency control product, while others offer separate products for regulation up (capacity to increase production) and regulation down (capacity to reduce production). In this paper, both types of frequency control AS are used.

2.2.2. Spinning reserves

Spinning reserves, sometimes also called "synchronous Reserves", are supplied by generation units that are online but not at full capacity, so they can quickly increase their output power and provide additional capacity to the system. Typically, generation units participate in spinning reserves increase their output power within 10 to 15 minutes of receiving instructions, depending on market details to help the system deal with forced outages or other potential accidents. [22].

2.2.3. Non-spinning reserves

Non-spinning reserves, sometimes referred to as "Supplemental Reserves", are used to help the system recover from possible unplanned problems and failures. There is usually 10 to 30 minutes' time to provide non-spinning reserves so offline generators can provide this AS if these units be able to start up and increase their output in the desired time [22].

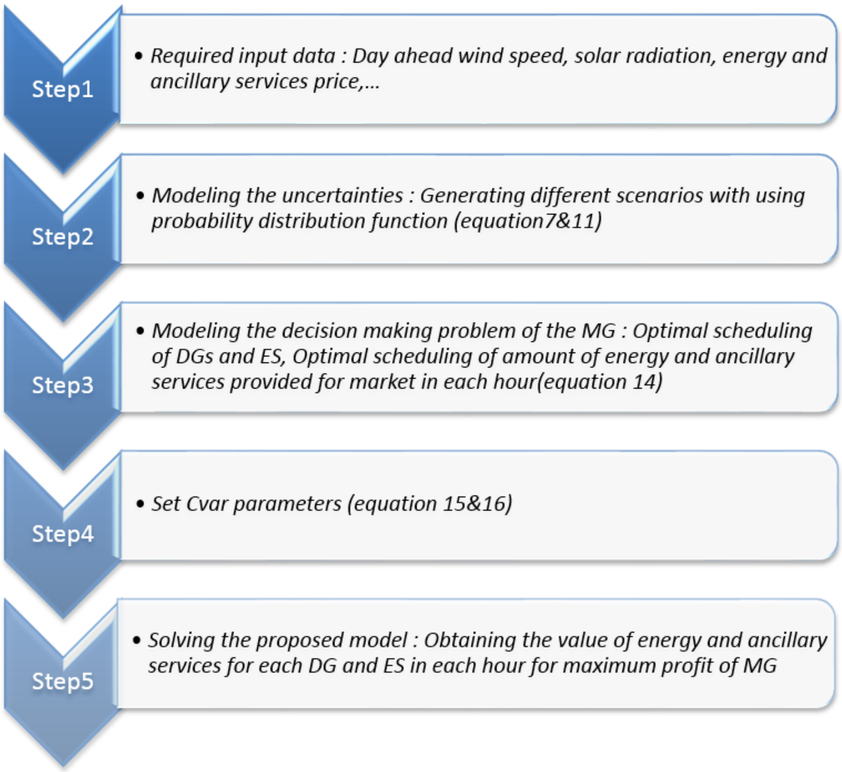

Fig. 2. Schematic diagram of the proposed bidding strategy

2.3. Profit of AS

The benefits of participating in AS markets consist of two parts. The first part of the AS contracts and the second part of the call for AS.

2.3.1. Reserve Capacity Benefit

The reserve capacity of generators participates in the AS market of MG, should pay for the reserve service, regardless of whether or not the reserve capacity is used in the actual operation period. The reserve capacity benefit can be expressed as [23,24]:

$$\mathrm{R}_{as} = P_{as}.E_{as} \quad (1)$$

2.3.2. Reserve Generation Benefit

In the EM when a failure occurs or consumption is more than generation, generators can be serviced as reserve generation and the reserve generation benefit can be expressed as [23,24]:

$$R_{asg} = P_{asg}.E_{asg} - c_{asg} \quad (2)$$

2.4. Cost function of generators

2.4.1. Cost function of GT

Generator curves are generally represented as cubic or quadratic functions and piecewise linear functions. GT uses a quadratic fuel cost function such as the fuel cost curve [25]:

$$C_{GT} = b_1 \times E^2 + b_2 \times E + b_3 \quad (3)$$

2.4.2. Cost function of WT and PV

The cost function of $WT\ and\ PV$ includes the initial investment costs of the power plant and the costs of operation and maintenance (O&M) of the amount of energy produced (excluding land costs) [26].

$$C_s = ((a_s \times I_s) + G_s) \times E \quad (4)$$

$$C_w = ((a_w \times I_w) + G_w) \times E \quad (5)$$

$$a = \frac{\gamma}{[1-(1+\gamma)^{-N}]} \quad (6)$$

2.5. Uncertainties

RES are the core part of MGs, but use those faces challenges. The uncertainty of RES is quite influential in the decision of MGs to bidding in the energy and AS markets. In different studies, different PDFs such as Gumbel, Weibull, lognormal, Beta have been used to model these uncertainties. In this paper, Weibull distribution is used to model wind speed and Beta distribution is used to model solar radiation.

2.5.1. Solar radiation uncertainties

The energy source of PV is sunlight, so the output power of PV directly depends on the amount of solar radiation. Sunlight is varying on different days and hours and usually predicting the amount of solar radiation is uncertain. In this paper, the Beta PDF is used to model solar radiation [26]. This function is represented in Eq. (7)

$$f_{gs} = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\, r^{(\alpha-1)}(1-r)^{\beta-1} & , 0 \le r \le 1, \alpha \ge 0, \beta \ge 0 \\ 0 & , otherwise \end{cases} \tag{7}$$

The α and β parameters are represented in Eq. (7) in terms of the average (μ) and standard deviation (σ) of solar radiation for the period under study [26].

$$\beta = (1-\mu)\frac{(\mu \times (1-\mu))}{\sigma^2} - 1 \tag{8}$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \tag{9}$$

The output power from PV for different solar irradiation is represented in equation (10) [14].

$$E_{pv} = E_{pvr} \times \frac{r}{r_{std}} \qquad \text{solar irradiation level W/ m}^2 \tag{10}$$

2.5.2. Wind speed uncertainties

WT converts wind into electrical energy, so wind is the main source of power for these turbines. The output power of these turbines is directly related to wind speed. Accurate wind speed estimation is necessary to predict the output of these turbines, but these estimates are always uncertain. The Weibull PDF can be used to model this uncertainty [27,28]. This function is represented in Eq. (11) where C is a scale index equal to $\frac{2}{\sqrt{\pi}} \times v_{ave}$, and v_{ave}, is the average incident wind speed at a particular location.

$$f_{gw} = (\frac{k}{c}) \times \left(\frac{v}{c}\right)^{k-1} \times \exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{11}$$

The output power from a WT for different wind speed is represented in equation (12) [29]

$$p_w = \begin{cases} 0 & v \le v_{in} \;\; or \;\; v \ge v_{out} \\ \frac{v - v_{in}}{v_r - v_{in}} \times p_{wr} & v_{in} \le v \le v_r \\ p_{wr} & v_r \le v \le v_{out} \end{cases} \qquad \text{wind speed level m/ s} \tag{12}$$

2.6. Objective function

In order to maximize the profit of the MG, the income difference from the cost should be maximized. The objective function of this is as Eq(13).

$$mazimize\ profit = mazimize \sum_{t=1}^{24}(income - cost) \tag{13}$$

The objective function for maximizing the profit of the MG is expressed as follows.

$$profit = \sum_{s=1}^{s} \pi(s)$$

$$\times \sum_{n=1}^{n} \left[\begin{bmatrix} (P_s \times E_{n,s}^{e}) \\ + (oP_{ru,s} \times E_{n.s}^{ru}) + \lambda_{ru}(P_{ru,s,} \times E_{n,s}^{ru}) \\ + (oP_{sp,s} \times E_{n,s}^{sp}) + \lambda_{sp}(P_{sp,s} \times E_{n,s}^{sp}) \\ + (oP_{ns,s} \times E_{n,s}^{ns}) + \lambda_{ns}(P_{ns,s} \times E_{n,s}^{ns}) \\ + (oP_{rd,s} \times E_{n,s}^{rd}) + \lambda_{rd}(P_{rd,s} \times E_{n,s}^{rd}) \end{bmatrix} \right.$$

$$\left. - \begin{bmatrix} (1 - \lambda_{ru} - \lambda_{rd} - \lambda_{sp}) \times C_n\left(E_{n,s}^{e}\right) \\ +\lambda_{ru} \times C_n\left(E_{n,s}^{e} + E_{n,s}^{ru}\right) \\ +(\lambda_{sp} - \lambda_{ns}) \times C_n\left(E_{n,s}^{e} + E_{n,s}^{sp}\right) \\ + \lambda_{ns} \times C_n\left(E_{n,s}^{e} + E_{n,s}^{sp} + E_{n,s}^{ns}\right) \\ + \lambda_{rd} \times C_n\left(E_{n,s}^{e} - E_{n,s}^{rd}\right) \end{bmatrix} \right] \quad (14)$$

Where Eq. (14) consists of two parts, income and cost. The income part includes five terms. The first term indicates the income of selling energy. The second term illustrates income of participating in regulation market and invoking reserve with considering probability of call. The third, fourth and fifth terms are similar term two for spinning reserve, non-spinning reserve and regulation down.

The cost part consists of five terms. The first term is illustrating the operation cost of the DGs just in the EM. The second term indicates the cost of the DGs when participating in regulation up. If a DG participates in energy and regulation up simultaneously, operational cost of the DG consisting energy power plus regulation up power. The third term illustrates the cost of the DGs when participate in spinning reserve considering when grid needs for non-spinning reserve, does not stop spinning reserve. The fourth term models the cost of the DGs when participating in non-spinning reserve. The fifth term models the cost of the DGs when participating in regulation down.

2.7. Risk management

Due to the uncertainties of RES, energy and AS price and energy consumption different conditions may occur from the predicted conditions. In competitive markets, risk management plays an important role in bidding strategy. For this purpose, the CVaR method can be used because, besides being a coherent risk measure, it can be expressed using a linear formulation [30].

CVaR considers expected profit such that less than $(1-\delta)\times 100\%$ scenarios with lowest profits [12] and CVaR index is added to the objective function and controls the effect of uncertainties on the objective function. Normally the confidence level is assumed to be between 0.9 and 0.99. CVaR is presented as follows [12,31]:

$$CVaR = var - 1/(1-\delta) \times \sum_{s=1}^{s} \pi_s \times \eta_s \tag{15}$$

The new objective function formulation of MG is given in equation (16)

$$maximize = w \times profit + (1-w)\ cvar \tag{16}$$

2.8. Constraint

2.8.1. Grid and generators constraint

Eq. (17) is used to model the limitations of the generation units where the total amount of the AS and energy provided by the DGs is limited between their minimum and maximum output power. Eqs. (18) - (22) are used to model the limitations of the generation units where the amount of each AS and energy provided by the DGs is equal or bigger than zero [2,32,33]. Relations of (23) through (27) provide the constraints of market requirement to energy and AS. The sum of the amount of energy and each AS provided by all the DGs is equal or less than the market requirement. Eq. (28) is used to model the limitations of the generation units where the sum of the amount of regulation down and minimum generation power must be less than amount of energy. Eqs. (29) - (30) are used to model the technical constraints, including ramp up/down constraints. [18]

$$E_n^{min} \le E_n^e + E_n^{ru} + E_n^{sp} + E_n^{ns} \le E_n^{max} \tag{17}$$

$$0 \le E_n^e \tag{18}$$

$$0 \le E_n^{ru} \tag{19}$$

$$0 \le E_n^{sp} \tag{20}$$

$$0 \le E_n^{ns} \tag{21}$$

$$0 \le E_n^{rd} \tag{22}$$

$$0 \le \sum_{n=1}^{n} E_n^e \le E_{req}^e \tag{23}$$

$$0 \le \sum_{n=1}^{n} E_n^{ru} \le E_{req}^{ru} \tag{24}$$

$$0 \le \sum_{n=1}^{n} E_n^{sp} \le E_{req}^{sp} \tag{25}$$

$$0 \le \sum_{n=1}^{n} E_n^{ns} \le E_{req}^{ns} \tag{26}$$

$$0 \leq \sum_{n=1}^{n} E_n^{rd} \leq E_{req}^{rd} \tag{27}$$

$$0 \leq E_n^{rd} \leq E_n^{E} - E_n^{min} \tag{28}$$

$$E_n(t) - E_n(t-1) \leq UR_n \tag{29}$$

$$E_n(t-1) - E_n(t) \leq DR_n \tag{30}$$

2.8.2. Storage constraint

Constraint (31) represents the relationship between stored energy and charging/discharging power [8]. Constraints (32) – (33) represent the limitations of charging and discharging power, and the stored energy of the storages, respectively [3]. Eq. (35) is used to model the limitations of the storage unit where the total amount of the AS and energy provided by the storage unite is limited between the zero and maximum output power of storage. Constraint (36) indicates that the storage device cannot charge and discharge at the same time [3].

$$E_{st}(t) = E_{st}(t-1) + \eta^{st} \times E_{st}^{sh} - \frac{E_{st}^{dsh}}{\zeta^{st}} \tag{31}$$

$$E_{st}^{sh} \leq E_{st}^{sh\,\max} \tag{32}$$

$$E_{st}^{dsh} \leq E_{st}^{dsh\,\max} \tag{33}$$

$$E_{st} \leq E_{st}^{\max} \tag{34}$$

$$0 \leq E_{st}^{e} + E_{st}^{ru} + E_{st}^{sp} + E_{st}^{ns} \leq E_{st} \tag{35}$$

$$s_{sh} + s_{dsh} \leq 1 \tag{36}$$

2.8.3. Risk management constraint

The following constraints in equations (37) - (38) must be observed for the calculation CVaR [14].

$$var - profit_s \leq \eta_s \tag{37}$$

$$\eta_s \geq 0 \tag{38}$$

3. Case study

For the case study, the Electric Reliability Council of Texas (ERCOT) market [34] simulation has been done in order to determine the participation of each generator in all of the mentioned markets and also to present the bidding curve based on the real data of 12/7/2020. The Weibull and Beta PDFs of the Texas region were used to scenario making of wind speed and solar radiation.

3.1. Basic data of MG

The simulated MG contains two GT units, WT, PV and ESS. The economic, technical and specification data are representing in table 2, table 3, table 4 and table 5.

Table 2. Data of PV

Parameter	value	Unit
E^{max}	2	MW
Irradiance at STC	1000	W/m^2
I	232	$\$/MWh$
G	7.5	$\$/MWh$
γ	0.09	-----
N	20	Year

Table 3. Data of WT

Parameter	value	Unit
E^{max}	1	MW
v_{in}	3	m/s
v_r	12	m/s
v_{out}	22	m/s
I	240	$\$/MWh$
G	5.77	$\$/MWh$
γ	0.09	------
N	20	Year

Table 4. Data of GT units

parameter	GT1	GT2	unit
E^{max}	1	2	MW
E^{min}	0.2	0.4	MW
UR	0.5	1	MW
DR	0.5	1	MW
b_1	0.02	0.03	-
b_2	2	1.5	-
b_3	5	6	-

Table 5. Data of ESS

Parameter	value	Unit
$E_{st}^{sh\max}$	2	MW
$E_{st}^{dsh(\max)}$	2	MW
η^{st}	90	%
ζ^{st}	90	%
$E_{st}^{\max}$	6	MW

3.2. Weather data

The weather data of Texas on 12th July 2020 is used for case study [35]. Wind speed and solar radiation are indicated in Fig. 3 and Fig. 4.

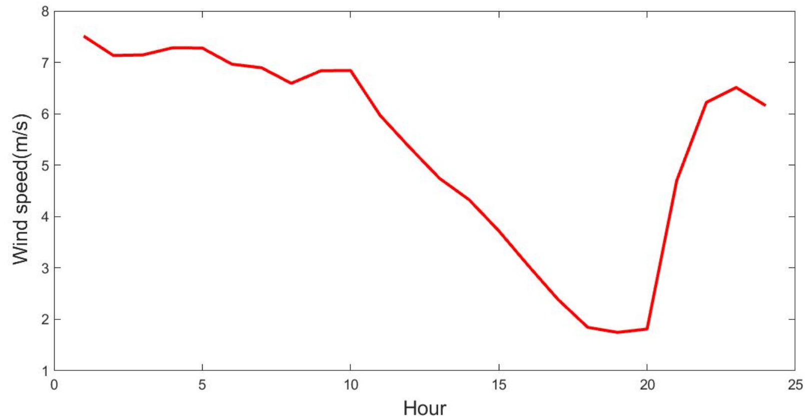

Fig. 3. Wind speed m/s

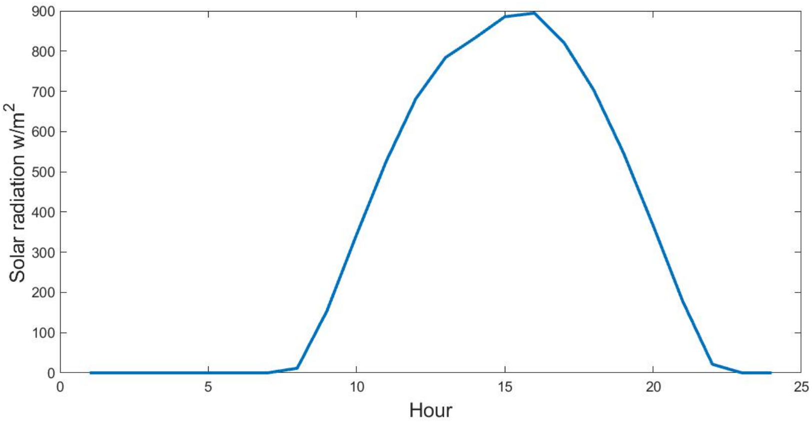

Fig. 4. solar radiation w/m^2

Weibull, and Beta PDFs are used to scenario generation of wind speed and solar radiation. The wind speed or solar radiation PDFs are divided into some intervals. Each interval is related to a specific scenario. For example, for wind speed the probability of S_{th} wind scenario, π_s, is calculated as Eq. (39) :

$$\pi_s = \int_{v_{min}}^{v_{max}} f_{gw}(v)\, dv \tag{39}$$

It is worth mentioning that v_{max} and v_{min} are the boundaries of S_{th}interval or S_{th} wind scenario [29,33]. ‘In this paper, distributions are supposed to be divided to three intervals. The historical data of wind speed or solar radiation in each time step is considered as the mean value of PDFs.

Therefore, the probability of each interval of this PDFs is calculated for different wind speeds or solar radiations by Eq. (39). ‘EasyFit’ is used for plot and calculate this PDFs and probability of each interval [36]. Three main scenarios of Wind speed and solar radiation are indicated in Fig. 5 and Fig. 6.

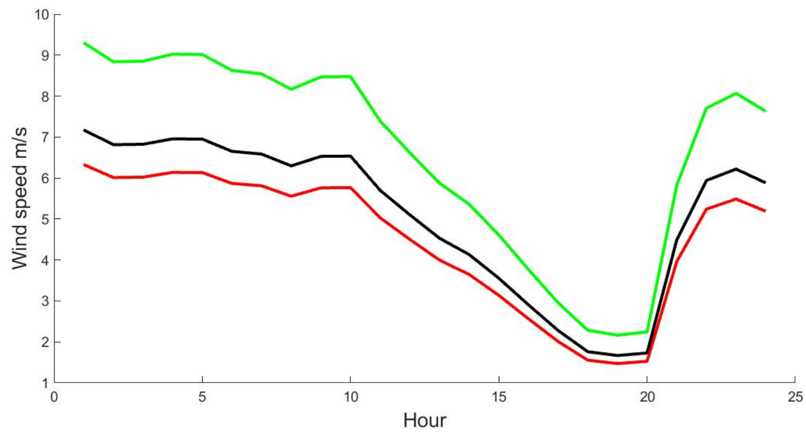

Fig. 5. Wind speed scenario m/s

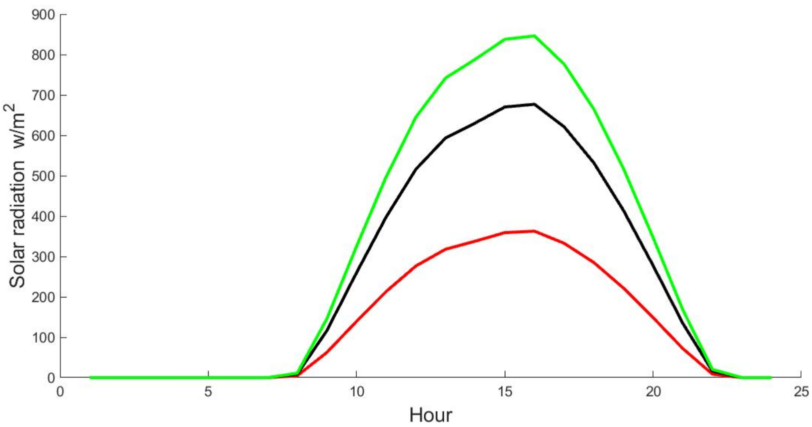

Fig. 6. Solar radiation scenario w/m^2

3.3. Data of market

In the DAM, every day at 6 o'clock, ERCOT publishes system information related to energy and AS. Qualified units must submit their bids until 10 for participation in the energy and AS markets. The market will be held from 10 to 13:30 o'clock and then the market results will be announced [22].

3.3.1 Market price

The market clearing price (energy and AS) and offer price of AS for ERCOT market, 12th July 2020 are indicated in Fig. 7 and Fig. 8 [34,37]. As is clear in Fig. 7 and Fig. 8 energy and AS prices are high between 14 and 19 due to high energy consumption.

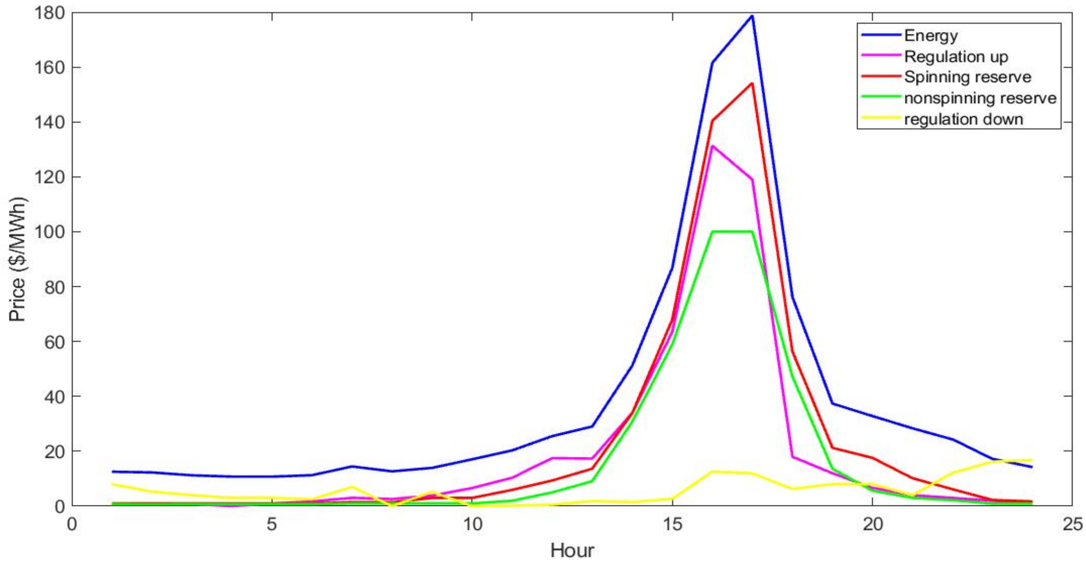

Fig. 7. Energy and AS price ($/MWh)

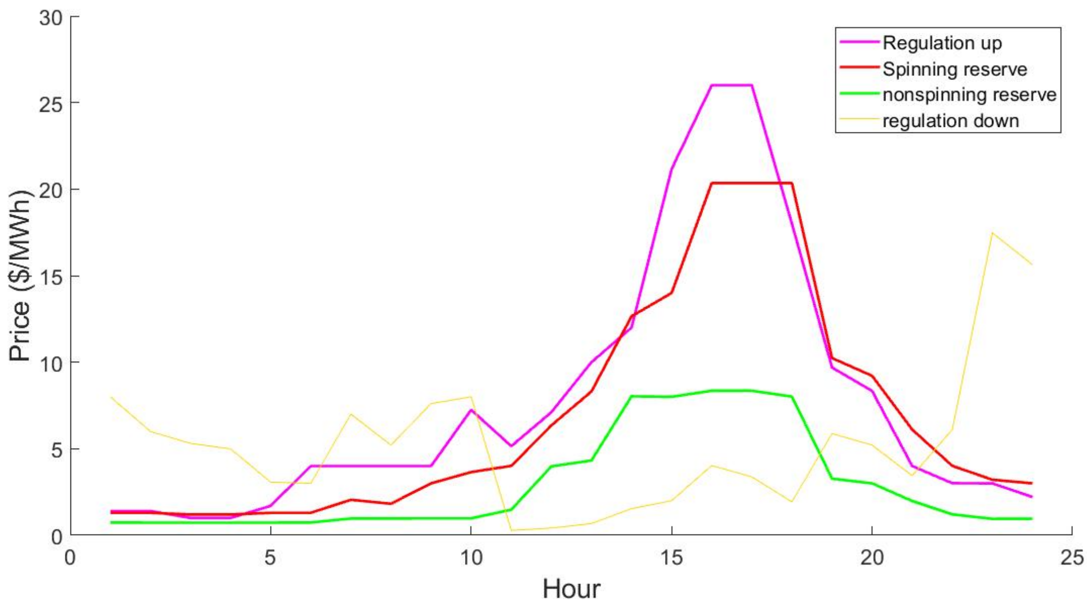

Fig. 8. AS offer price ($/MWh)

3.3.2. Probability of call AS

Each year, ERCOT market publishes annual energy consumption and the average need for AS for each month. Fig.9 Indicates the average need for AS for July 2020 [34,37].

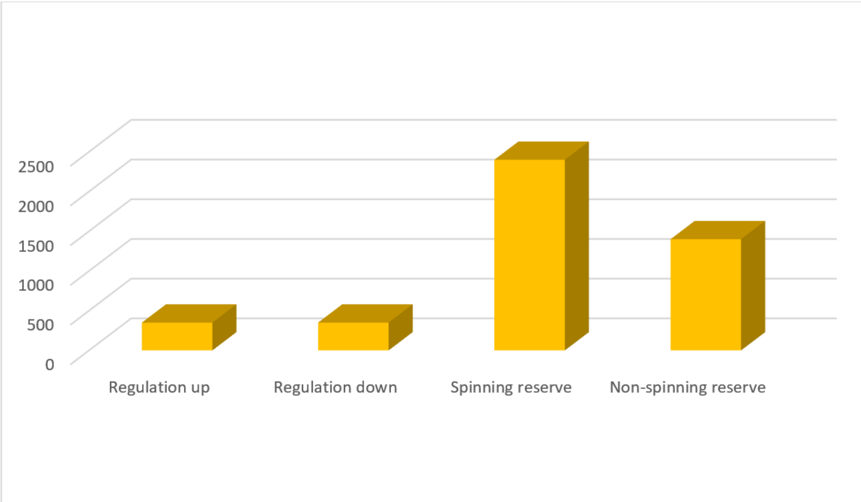

Fig. 9. Hourly average AS requirement (MWh)

By dividing the hourly average AS requirement by the average hourly energy consumption, the probability of call AS can be calculated as Eq. (40).

$$\lambda = \frac{\text{hourly average AS requirement}}{\text{average hourly energy consumption}} \quad (40)$$

The probability of call AS data is provided in Table 6 respectively [34].

Table 6. Probability of call AS

Type of AS	λ
Regulation up	0.0069
Regulation down	0.0067
Spinning reserve	0.055
Non-spinning reserve	0.032

3.4. Result

3.4.1 Result of case 1

In the first case, MG participation in energy and AS markets is simulated for 24 hours for 12/7/2020. Fig. 10 to Fig. 13 indicate the amount of participation of each unit in different markets, Fig. 14 indicates the amount of charge and discharge of storage and finally Table 7 indicates the total bidding of MG units in different markets. According to the results, RES have more participation in the EM, on the other hand, GTs only participate in the EM when the energy rate is high, because the operating cost of RES is lower than GTs, so participation in the AS market has more profit for GTs.

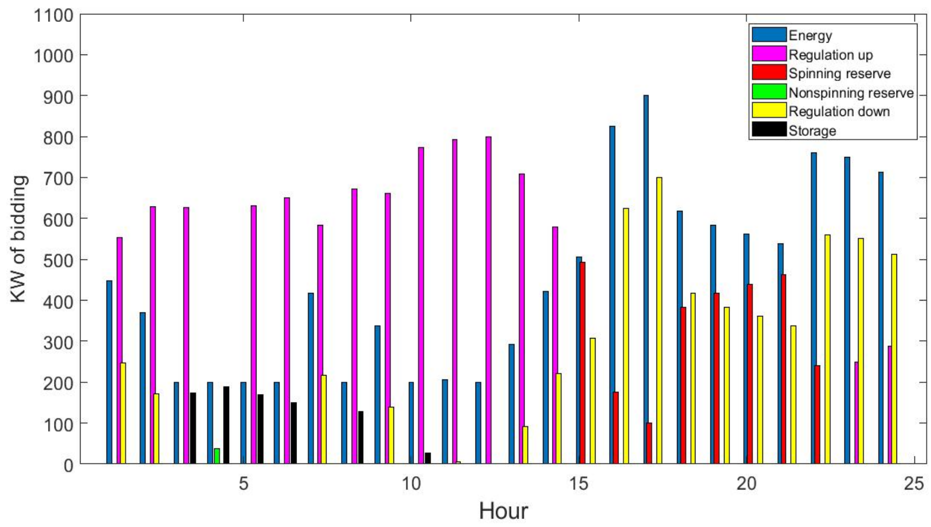

Fig. 10. GT1 bidding in case 1

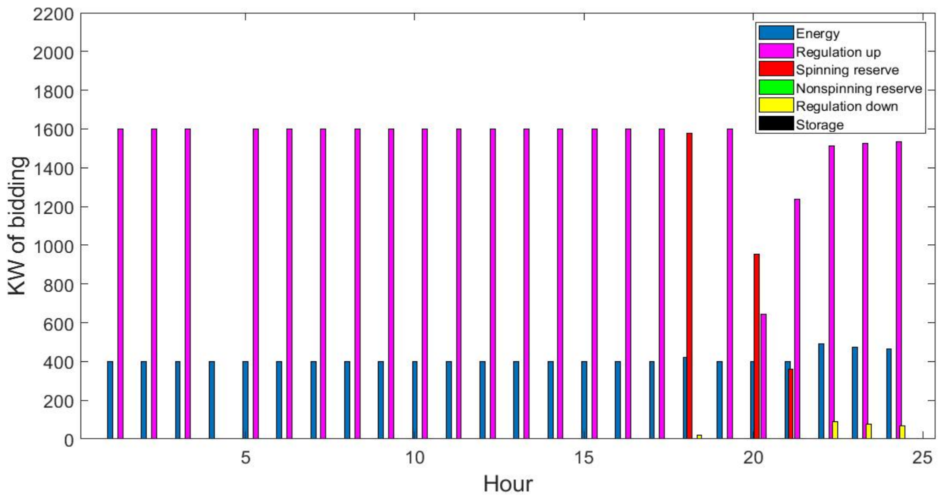

Fig. 11. GT2 bidding in case 1

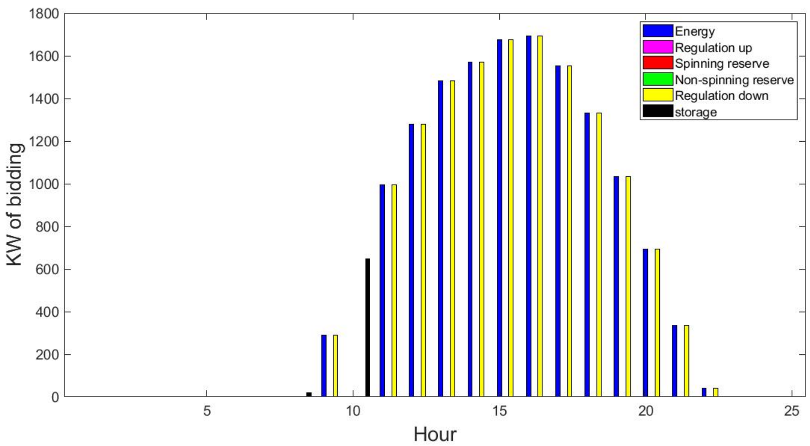

Fig. 12. PV bidding in case 1

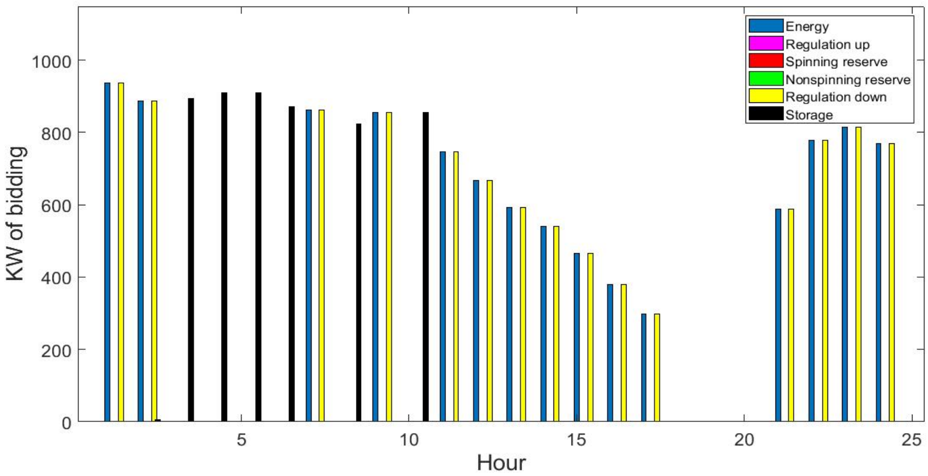

Fig. 13. WT bidding in case 1

As indicated in Fig.14, during the hours when energy is cheap, such as the early hours of the day, the MG stores energy and sells it during the hours when energy is expensive. At 4 o'clock, the price of energy and AS is low in all markets, so the MG stores almost all of its renewable production at this hour and GTs bidding just minimum power to be online. Due to the difference in capacity and the cost function of GT1 and GT2, their behavior is also different.

In Fig.15, the cost curve of energy production of these two units, indicates energy production in the second unit is more expensive, so this unit has more participation in the AS market. All units participate in the regulation down market with all of their power, as it does not increase their production costs, but it should be noted that the market may require a limited amount of these services (no limit is assumed in this paper).

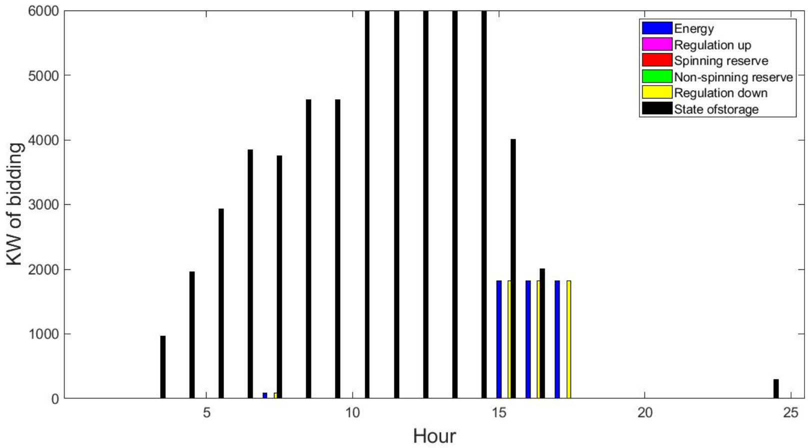

Fig. 14. ESS state and participation at the end of hour and participation in case 1

Table 7. MG total bidding in case 1(MW)

Hour / Market	Energy	Regulation up	Regulation down	Spinning reserve	Non-spinning reserve	storage
1	1.4747	2.1532	1.1846	0.0000	0.0000	0.0000
2	1.2772	2.2288	1.0581	0.0000	0.0000	0.0050
3	0.8864	2.2259	0.0000	0.0001	0.0001	1.0678
4	0.8387	0.0001	0.0000	0.0000	0.0375	1.1007
5	0.8153	2.2312	0.0000	0.0000	0.0000	1.0787
6	0.8129	2.2493	0.0000	0.0000	0.0000	1.0216
7	0.8367	2.1825	1.1708	0.0000	0.0000	0.0000
8	0.8047	2.2718	0.0000	0.0000	0.0000	0.9731
9	0.8705	2.2617	1.2842	0.0000	0.0000	0.0000
10	0.8678	2.3724	0.0002	0.0000	0.0000	1.5314
11	0.8552	2.3935	1.7474	0.0000	0.0000	0.0000
12	0.8272	2.4000	1.9480	0.0000	0.0000	0.0000
13	0.7895	2.3082	2.1677	0.0000	0.0000	0.0000
14	1.4000	2.1784	2.3325	0.0001	0.0000	0.0000
15	6.0023	1.6000	4.2645	0.4936	0.0000	0.0000
16	4.9051	1.6000	4.5150	0.1751	0.0000	0.0000
17	1.6908	1.6000	4.3686	0.0995	0.0000	0.0000
18	0.6000	0.0000	1.7684	1.9616	0.0000	0.0000
19	1.1719	1.6000	1.4180	0.4170	0.0000	0.0000
20	1.5866	0.6447	1.0540	1.3942	0.0000	0.0000
21	1.2214	1.2388	1.2619	0.8233	0.0000	0.0001
22	1.8095	1.5110	1.4671	0.2399	0.0000	0.0000
23	1.8966	1.7747	1.4392	0.0000	0.0000	0.0000
24	1.5305	1.8210	1.3489	0.0000	0.0000	0.0000

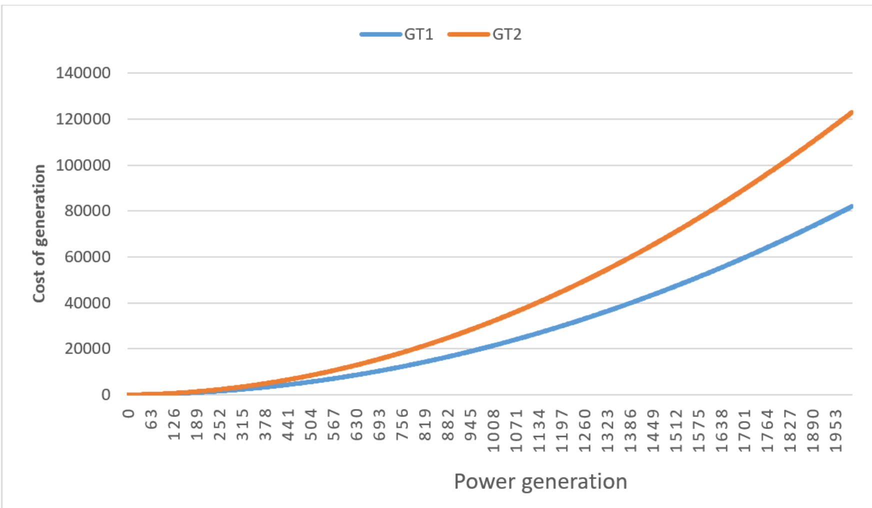

Fig. 15. Operation cost of GT1 and GT2

3.4.2. Result of case 2

In the second case, the behavior of the MG at different energy prices is investigated. Energy prices are proposed to be 50%, 100% and 150% of the unit price. In Fig.16, the total participation of the MG in the EM is indicated for different prices.

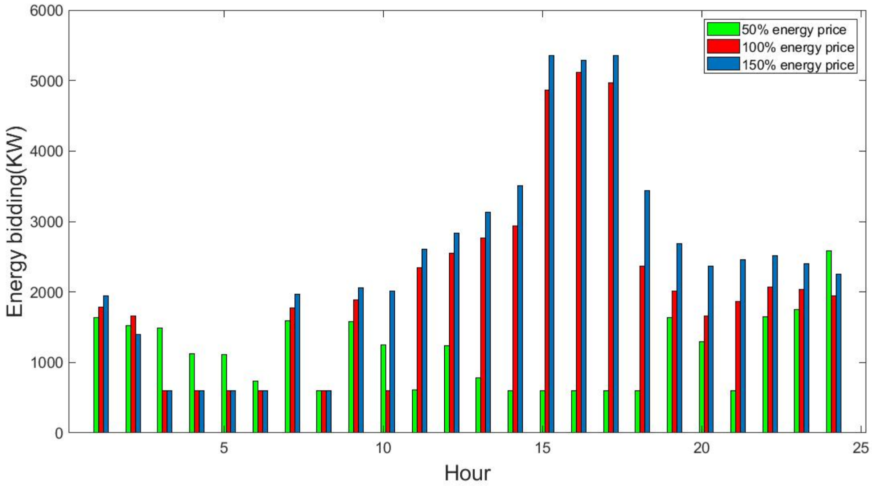

Fig. 16. MG bidding in EM for different prices case 2

Fig 16 indicates by increasing energy prices, MG participation in the EM increase. In some early hours of the day, due to the fact that the price of energy during peak hours in the second and third situations is much higher than the first situation, the MG stores electrical energy and sells it during peak hours, so at early hours of the day MG participation in the EM in first situation is more than situation 2 and 3. Fig.7 shows that the price of energy at 7 o'clock is higher than the hour before and after that, so the participation in the EM at this hour is higher than the hour before and after that. Fig17 indicates stored energy in each hour.

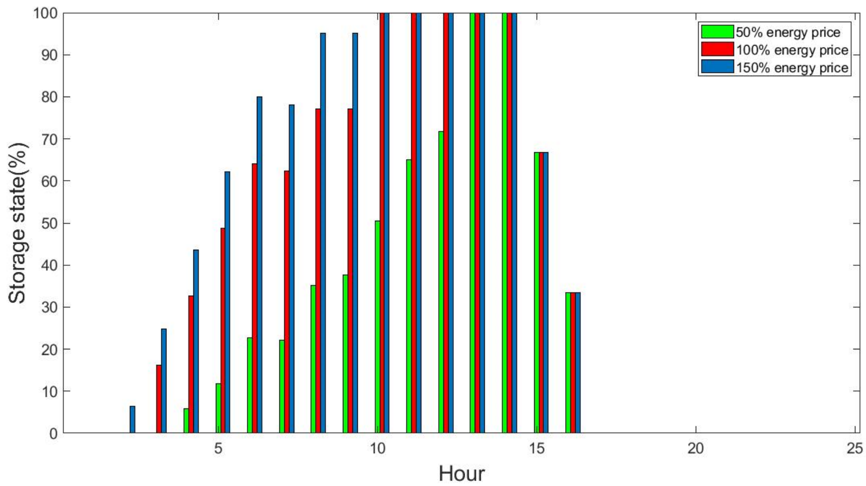

Fig. 17. Charge state of storage for different price of energy case 2

In the second and third situations, due to the high price of energy, during the peak load, MG stores energy from first hours of the day that energy is cheap, in order to earn more income by selling it during peak hours. Profits from the sale of energy at a higher price cause the MG to ignore storage losses. Fig. 7 shows that the price of energy at 7 o'clock is higher than the hour before and after that, so MG decides to sell electricity in the market and does not store it and energy storage state does not increase at 7 o'clock. For the same reason, energy storage is not done at 1 and 2 o'clock, just in third situation at 2 o'clock MG decides to store energy because of higher price of energy in pick hours than situations one and two. Fig.18 illustrates the bidding curve of MG at 10 o’clock and Fig.19 illustrates the bidding curve of GT1 at 15 o’clock. It is clear that in both curves, as energy prices rise, the MG tends to more participation in the energy market.

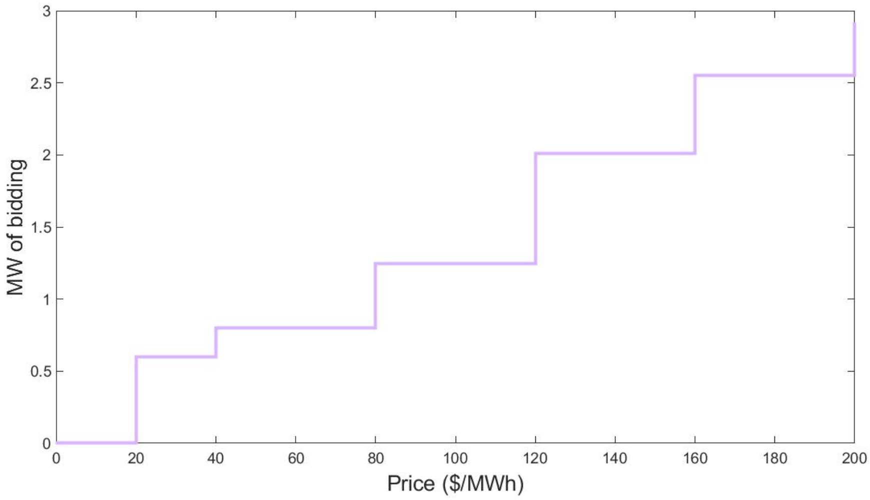

Fig. 18. Bidding curve of MG at 10 o’clock

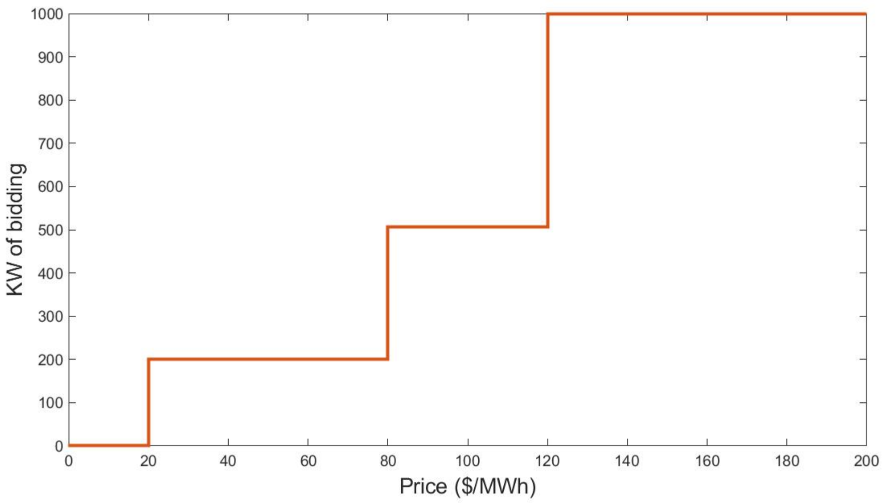

Fig. 19. Bidding curve of GT1 at 15 o’clock

4. Conclusion

Microgrids can maximize their profit by simultaneously participating in the energy and ancillary services (AS) markets, in addition to maintaining the security and stability of the power grid. For optimal bidding, the uncertainties of wind speed, solar radiation and probability of call AS should be carefully considered. The simulation was based on real-world data on different electricity prices for the ERCOT market and 'conditional value at risk' method used for risk management. The simulation results illustrate that the units that have higher operating costs are more willing to participate in the AS market and just participate in the energy market during the hours when energy prices are high and cheaper units have more involvement in AS. Also, expensive generators such as gas turbines, with different cost functions and designs, have different amount of participation in different markets. The probability of calling AS presents that the generator is not always active with full contract capacity in the AS market, so its operating cost is reduced and it can be more profitable than the energy market, especially for expensive generators. for instance, probability of calling regulation up is 0.0069 and gas turbine 2 participates in this market approximately all the times. Bidding curves for different energy prices illustrate that as the price of energy increases, the participation in it also increases, for example, with an increase in energy prices by 9 times (20 to 180 ($/MWh)), microgrid's participation in energy market increases from 0.6 to 2.6 MW (it rises about 330%). Also, with the increasing difference of energy prices at different hours, the amount of energy storage for sale during expensive hours' increases. For example, with a 50% increase in energy prices, energy storage begins in the early hours of the day and at a higher rate, because in the middle hours the difference in energy prices is maximum. Therefore, despite the energy losses in storage, the microgrid can maximize its profitability by storing energy in cheap hours (generally in the early hours of the day) and selling it in the hours when energy prices are higher.

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