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Smart microgrid energy and reserve scheduling with demand response using stochastic optimization

Alireza Zakariazadeh [a], Shahram Jadid [a], Pierluigi Siano [b,*]

[a] Electrical Engineering Department, Iran University of Science and Technology (IUST), Iran
[b] Department of Industrial Engineering, University of Salerno, Fisciano, Italy

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ABSTRACT

Demand side participation is one of the important resources that help the operator to schedule generation and consumption with lower cost and higher security. Customers can participate in both energy and reserve operational scheduling and earn benefit from reducing or shifting their consumption. In this paper, a novel stochastic energy and reserve scheduling method for a microgrid (MG) which considers various type of demand response (DR) programs is proposed. In the proposed approach, all types of customers such as residential, commercial and industrial ones can participate in demand response programs which will be considered in either energy or reserve scheduling. Also, the uncertainties related to renewable distributed generation are modeled by proper probability distribution functions and are managed by reserve provided by both DGs and loads. The proposed method was tested on a typical MG system comprising different type of loads and distributed generation units. The results demonstrate that the adoption of demand response programs can reduce total operation costs of a MG and determine a more efficient use of energy resources.

Introduction

Intelligent electrical grids with renewable energy sources have attracted increasing public attention in recent years. Green (solar and wind in particular) energy production is supposed to increase significantly in the next years. Microgrids (MGs) can be key solutions for integrating renewable and distributed energy resources, as well as distributed energy-storage systems [1,2]. According to the United States Department of Energy (DOE) definition, a MG consists of a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries. A MG acts as a single controllable entity with respect to the grid and can connect and disconnect from the grid in order to operate in both grid-connected and islanded mode [3]. The MG concept has been essentially introduced in order to support a better renewable energy penetration into the utility grid, to respond to some grid issues, such as peak shaving, and to reduce energy costs [4–6]. So, MG can be located in LV or MV level base on distribution networks configurations and voltage levels. A MG can be at LV or MV level, however, in most of studies and projects, MGs are usually LV networks and are interconnected to the MV distribution network [7–9]. In order to achieve the full benefits from the operation of MGs, it is important that the integration of the distributed resources into the LV grids, and their relation with the MV network upstream, contribute to optimize the general operation of the system [9].

On the other hand, a huge penetration of renewable energy sources may affect reliable and secure operation of the MG due to the intermittent nature of these resources [10]. So, the microgrid operator (MGO) usually faces renewable generation uncertainty as well as load demand uncertainty. This increased uncertainty must be considered when determining the requirements for spinning reserve (SR) in order to protect the power system against sudden load and renewable generation changes [11]. In some approaches, the total amount of reserve requirement of the grid is determined before the energy scheduling and without considering the probabilistic behavior renewable resources. This method is named deterministic energy and reserve scheduling [11–14]. On the other hand, in the stochastic method, the uncertainties related to renewable generation and load demand are modeled by scenarios and the reserve scheduling is carried out based on the probabilities of scenarios [15,16]. Some studies evidenced that the stochastic method has lower operational costs if compared with the deterministic ones [11,17].

In [7], a smart energy management system (SEMS) was presented to optimize the operation of the MG. The paper also considered photovoltaic (PV) output in different weather conditions as

* Corresponding author. Tel./fax: +39 089964294.
E-mail addresses: zakaria@iust.ac.ir (A. Zakariazadeh), jadid@iust.ac.ir (S. Jadid), psiano@unisa.it (P. Siano).

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Nomenclature

Indices

t	index of optimization period, $t = 1, 2, \ldots, 24$
i	index of industrial customers, $i = 1, 2, \ldots, I$
b	index of commercial customers, $b = 1, 2, \ldots, B$
h	index of residential customers (home), $h = 1, 2 \ldots, H$
ty	index of shiftable appliances
k	index of steps in load reduction offer, $k = 1, 2, \ldots, K$
n, m	index of buses, $n = 1, 2, \ldots, N$
j	index of non-renewable DGs, $j = 1, 2, \ldots, J$
s	index of scenarios, $s = 1, 2, \ldots, S$
w	index of wind turbines, $w = 1, 2, \ldots, W$
pv	index of PV units, $pv = 1, 2, \ldots, Pv$

Variables

Binary variable

$u(j,t)$	on/off status (1/0) of the non-renewable DG j in period t
$us(j,t,s)$	on/off status (1/0) of the non-renewable DG j in period t and scenario s
$d(t,h,ty)$	on/off status (1/0) of home appliances ty at home h and in period t
$Y(t)$	1 if battery starts charging in period t and 0 otherwise
$X(t)$	1 if battery starts discharging in period t and 0 otherwise

Continuous variable

$Ecost$	total expected cost ($)
l_k^i	accepted load reduction of industrial customer i in step k of price-quantity offer package (kW)
$IC^E(i,t)$	total scheduled load reduction quantity prepared by the industrial customer i in period t (kW)
$IC^s(i,t,s)$	required load reduction quantity prepared by the industrial customer i in period t and scenario s (kW)
$IP^E(i,t)$	cost due to load reduction provided by industrial customer i in period t ($)
$IC^R(i,t)$	scheduled reserve provided by industrial customer i in period t (kW)
$IP^R(i,t)$	cost due to committing reserve provided by industrial customer i in period t ($)
$IP^s(i,t,s)$	cost due to load reduction provided by industrial customer i in period t and scenario s ($)
$CC^E(b,t)$	scheduled load reduction provided by commercial customer b in period t (kW)
$CC^s(b,t,s)$	required load reduction provided by commercial customer b in period t and scenario s (kW)
$CC^R(b,t)$	scheduled reserve provided by commercial customer b in period t (kW)
$CP^E(b,t)$	cost due to load reduction provided by commercial customer b in period t ($)
$CP^R(b,t)$	cost due to committing reserve provided by commercial customer b in period t ($)
$CP^s(b,t,s)$	cost due to load reduction provided by commercial customer b in period t and scenario s ($)
$RC^E(h,t)$	scheduled load reduction provided by residential customer h in period t (kW)
$RC^R(h,t)$	scheduled reserve provided by residential customer h in period t (kW)
$RP^E(h,t)$	cost due to load reduction provided by residential customer h in period t ($)
$RP^R(h,t)$	cost due to committing reserve provided by residential customer h in period t ($)
$RP^s(h,t,s)$	cost due to load reduction provided by residential customer h in period t and scenario s ($)
$P_{grid}(t)$	scheduled purchased energy from the main grid in period t (kW)
$C_{DG}(j,t)$	hourly fuel cost of non-renewable DG j in period t ($)
$Cs_{DG}(j,t,s)$	hourly fuel cost of non-renewable DG j in period t and scenario s ($)
$P_{DG}(j,t)$	scheduled active output power of non-renewable DG j in period t (kW)
$Ps_{DG}(j,t,s)$	active output power of non-renewable DG j in period t and scenario s (kW)
$R_{DG}(j,t)$	scheduled spinning reserve provided by non-renewable DG j in period t (kW)
$ENS(s,t)$	the amount of involuntarily load shedding in period t and scenario s (kW)
$Po_w(t)$	scheduled wind power of wind turbine w at hour t (kW)
$Po_{pv}(t)$	scheduled solar power of PV unit pv at hour t (kW)
$Loss(t)$	total network losses in period t (kW)
$SU(j,t)$	start up cost of non-renewable DG j in period t ($)
$P_B^+(t)$	scheduled battery discharge power in period t (kW)
$P_B^-(t)$	scheduled battery charge power in period t (kW)
$\|V(n,t)\|$	voltage amplitude at node n and in period t, p.u.
$\delta(n,t)$	voltage angle at node n and in period t
$P_{inj}(n,t)$	net injected active power to node n and in period t, p.u.
$Q_{inj}(n,t)$	net injected reactive power to node n and in period t, p.u.

Parameters

$P_L(t)$	total hourly demand of MG in period t (kW)
l_k^i	price offer of industrial customer i in step k ($/kW)
$q^{I,r}(i,t)$	reserve price of industrial customer i for being in standby in period t ($/kW)
L_{Max}^i	maximum quantity of load reduction offered by industrial customer i in period t (kW)
$CC_b^{max}(b,t)$	maximum quantity of load reduction offered by commercial consumer b in period t (kW)
$q^{C,E}(b,t)$	price offer of commercial customer b for energy reduction in period t ($/kW)
$q^{C,R}(b,t)$	price offer of commercial customer b for committing reserve in period t ($/kW)
$RC^{Max}(h,t)$	maximum quantity of load reduction offered by residential customer h in period t (kW)
$q^{R,E}$	price offer of residential customer h for energy reduction in period t ($/kW)
$q^{R,R}$	price offer of residential customer h for committing reserve in period t ($/kW)
$HDA(t,h,ty)$	power consumption of shiftable appliances ty at home h that turn on in period t ($\tau s \leqslant t \leqslant \tau e$), (kW)
$HDA^{Max}(h,ty)$	nominal power of shiftable appliance ty at home h (kW)
$f_w(v)$	Rayleigh probability distribution function
v	wind speed (m/s)
$f_b(\phi)$	beta probability distribution function
ϕ	solar irradiance (kW/m^2)
$P_{pv}(\phi)$	PV output power (kW) for irradiance ϕ
η^{pv}	efficiency of PV (%)
S^{pv}	total area of PV (m^2)
$P_w^s(s,t)$	wind turbine w output power in period t and scenario s (kW)
$P_{pv}^s(s,t)$	PV pv output power in period t and scenario s (kW)
$Ta_g^E(t)$	hourly electricity price ($/kW)
$C_{DGj}^R(j,t)$	reserve price of non-renewable DG j in period t ($/kW)
$VOLL(t)$	value of lost load in period t ($/kW)

P_{DGj}^{min}	minimum output power limits of non-renewable DG j (kW)
P_{DGj}^{max}	maximum output power limits of non-renewable DG j (kW)
Sc_j	start up cost of non-renewable DG j ($).
SOC_{Min}	minimum capacity of battery (kWh)
SOC_{Max}	maximum capacity of battery (kW h)
η^-	battery charge efficiency coefficients
η^+	battery discharge efficiency coefficients
N	total number of buses
$\lvert Y_{n,m} \rvert$	amplitude of element (n, m) in network admittance matrix
$\theta_{n,m}$	angle of $Y_{n,m}$

well as hourly electricity prices of the main grid. However, the method did not allocate reserve for renewable uncertainty and did not consider load participation in demand response programs. In [18], an energy management system (EMS) based on a rolling horizon (RH) strategy for a renewable-based MG has been presented. The EMS minimizes the operational and consequently provides the online set points for generation units. In [19], both emission and economic objectives were considered in MG operational scheduling. Mesh adaptive direct search algorithm was used to minimize the cost function of the system but demand side participation in energy market and wind and solar forecast errors were not considered. The application of a high reliability distribution system (HRDS) in the economic operation of a MG has been studied in [20]. HRDS, which offers higher operation reliability and fewer outages in MG, has been applied to looped networks in distribution systems.

The estimation model of spinning reserve requirement in MG was proposed in [21]. In the proposed method, the uncertainty of wind and solar generation is considered, as well as the unreliability of units and uncertainties caused by load demand. The approach aggregated various uncertainties in order to reduce the computational burden. The demand side reserve and load participation in energy markets was not considered in the model. A deterministic energy management system for a MG was proposed in [22]. The method includes advanced PV generators with embedded storage units and a gas micro-turbine. The scheduling was implemented in two parts: a central energy management of the MG and a local power management at the customer side. However, the reserve requirement estimation and demand response program in MG were not considered in this work. In [23], a model for MG optimal scheduling considering multi-period islanding constraints has been proposed. The objective of the problem is to minimize the MG total operation cost which comprises the generation cost of local resources and cost of energy purchase from the main grid. Benders decomposition method was employed to decouple the grid-connected operation and islanded operation problems. Islanding cuts were further utilized to coordinate these two problems. Mixed integer programming was used to model MG components, which included loads, generating units, and energy storage systems.

An environmental economic dispatch problem of smart MG using deterministic method has been proposed in [24]. The quantum genetic algorithm was used in order to minimize the operation cost and emission. But, the uncertain nature of renewable generation has not been taken into account in the energy scheduling. In [25], a MG energy management under cost and emission minimization has been presented in which optimal battery scheduling using by a fuzzy logic expert system has been investigated. Moreover, the uncertainty of the uncertainty of renewable generation and load demand has been taken into account. In [26], a stochastic framework for energy operation management of DGs in a grid-connected MG has been presented. The uncertainties of load forecast error, wind turbine generation, photovoltaic generation and market price has been considered in generation scenarios by using roulette wheel mechanism. However, the method did not focus on reserve scheduling and did not consider the role of DR in energy and reserve scheduling.

To the best of our knowledge, no stochastic energy and reserve scheduling method for a MG in which the demand side participation, as well as intermittent nature of renewable generation, has been reported in the literature. The main focus of this paper is, therefore, the proposal on an innovative stochastic energy and reserve scheduling method including multiple types of demand response programs in order to facilitate the participation of different types of customers in energy and reserve scheduling.

The rest of this paper is organized as follows. In Section 2 the advanced metering architecture of the microgrid is described. The demand response programs and renewable generations' uncertainty are modeled in Sections 3 and 4, respectively. The method formulation is detailed in Section 5. Simulation results are given in Section 6 and the paper is concluded in Section 7.

Advanced metering architecture of the microgrid

In order to practically apply the proposed method in a real MG, the two-way communication system between MG operator and consumers should be available [27–31]. As an available solution, the Advanced Metering Infrastructure (AMI) system of a real pilot project presented in [32,33] is introduced in order to make active all types of DR program that is used in the proposed method. The architecture of the smart metering system is shown in Fig. 1 and consists of:

- **Smart meters** with Power Line Carrier (PLC) communications, installed at the customer premises. They may be single phase or three phase smart meters. Also, the smart meter of medium and large customers could directly be connected to the utility by using GPRS.
- **Data concentrators** (DC) installed in 20 kV/400 V power transformers in order to manage all smart meters measured data from each installation. Data concentrators integrate PLC communications that exchange information with smart meters and communicate with central meter data management systems.
- **Meter data management system**, mainly meter data management & repository (MDM/R) systems in which the received unprocessed data from all meters or sensors are collected and processed in order to deliver the required data to MGO or DSO.
- **Customer energy management system**, mainly In Home Display (IHD) that shows the electricity consumption and the prices to customer. For residential customers, a Home Energy Scheduler (HES) system is also integrated into IHD. This system is explained in the residential customer sub-section.

Demand response participants

Different types of electricity customers with different electricity consumption behavior and pattern are considered in the proposed method. The types of customers and their involvement in DR programs are described in this section.

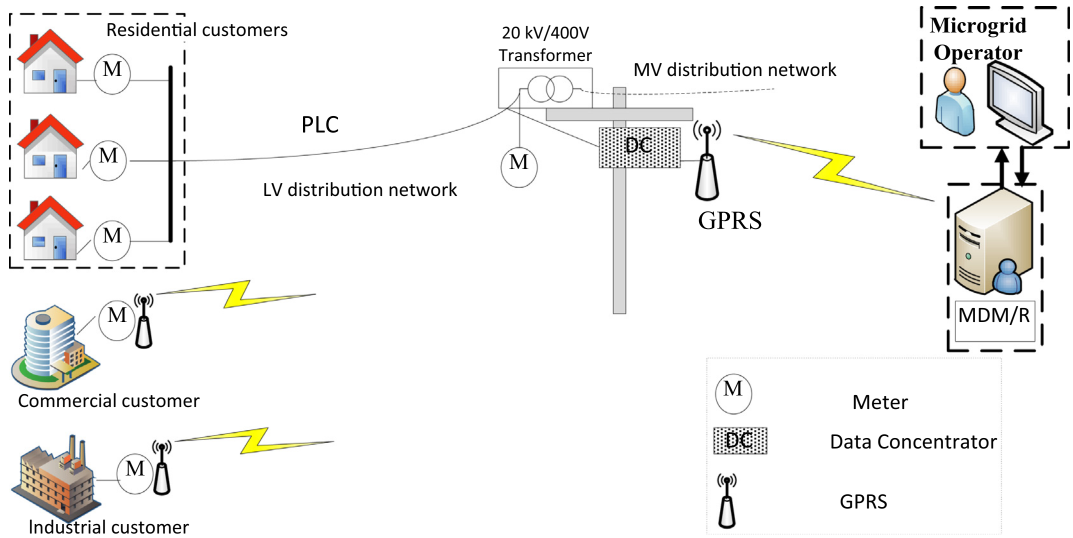

Fig. 1. Advanced metering architecture of the MG.

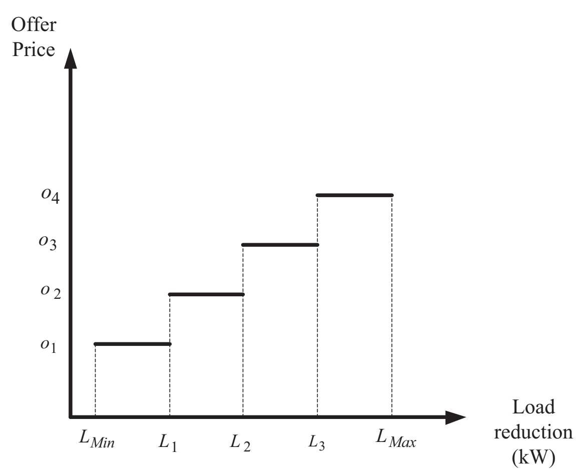

Fig. 2. The steps price-quantity offered package of an industrial customer.

Industrial customer

Industrial customers are usually characterized by heavy loads. As every factory comprises more than one production line, the energy curtailment in each production line has a distinct price offer pertaining to its production. So, industrial customers offer their load curtailment as a multi steps package.

Fig. 2 depicts a typical price-quantity offer package containing four pairs where o_k is the price offer at step k. For each hour, an industrial customer submits its price-quantity offer as a package. At each hour, L_{Max} is the maximum load reduction and L_{Min} is the minimum load reduction that an industrial customer can carry out. Let assume, for example, that in an energy scheduling procedure, L_3 kW of load reduction are accepted from an industrial customer. It is paid at o_1 for L_1, o_2 for $L_2 - L_1$, and o_3 for $L_3 - L_2$. The equations used for modeling the behavior of the ith industrial customer are the following ones from (1) to (4).

$$L^i_{Min} \leqslant l^i_1 \leqslant L^i_1 \tag{1}$$

$$0 \leqslant l^i_k \leqslant \left(L^i_k - L^i_{k-1}\right) \quad \forall\ k = 2, \ldots, K. \tag{2}$$

$$IC^E(i,t) = \sum_k l^i_k \tag{3}$$

$$IP^E(i,t) = \sum_k o^i_k . l^i_k \tag{4}$$

At each hour, the sum of the scheduled energy reduction and reserve provided by each industrial load should not be greater than its maximum load reduction offer $\left(L^i_{Max}\right)$. This means that the uncommitted load reduction capacity of each industrial customer in the energy scheduling can be scheduled for the reserve requirement. The reserve provided by each industrial customer is calculated as follows:

$$IC^E(i,t) + IC^R(i,t) \leqslant L^i_{Max} \tag{5}$$

$$IP^R(i,t) = IC^R(i,t) \times q^{I,R}(i,t) \tag{6}$$

Commercial customer

Commercial consumers always offer the maximum amount of possible load reduction at the desired price for curtailment to MGO. The equations used for modeling the behavior of the commercial customer b, participating in both energy reduction and reserve commitment are given as follows:

$$CC^E(b,t) + CC^R(b,t) \leq CC^{max}_b(b,t) \tag{7}$$

$$CP^E(b,t) = CC^E(b,t) \times q^{C,E}(b,t) \tag{8}$$

$$CP^R(b,t) = CC^R(b,t) \times q^{C,R}(b,t) \tag{9}$$

Residential customer

In the proposed method, it has been assumed that every house in the MG control area has an automatic controller and energy management system. It includes a Home Energy Scheduler (HES) that is a package including smart meter, microcontroller and an In-Home Display (IHD). The HES also receives some command signals from the MGO and is able to send some data signal to it. As most of people are not interested to pay attention to their energy consumption and prices, they do not perform energy management activities. The HES gives a remote control of the in-home appliances to the MGO to allow faster regulation and control according to the current situation.

In a typical house, there are different electric appliances. Residential demand response programs usually try to achieve a reduction and/or a shifting of energy consumption. Reducing consumption is performed by interruptible appliances like heating, ventilation, and air-conditioning (HVAC) systems, lamps and refrigerators. In this type of household appliances, the energy consumption is reduced in a specific period but is not shifted to another time period. The shiftable appliances such as dishwasher and washer-dryer can shift their working period to another time period, instead.

The MGO receives HES data through the communication link. Then, the MGO considers the residential customer load curtailing or shifting in the scheduling program. Constraint (10) shows that sum of energy reduction and reserve commitment of each residential customer at every hour should be lower or equal to the maximum amount of its offers. The equations used for modeling the behavior of the hth residential customer are the following ones.

$$RC^{E}(h,t) + RC^{R}(h,t) \leq RC^{Max}(t) \tag{10}$$

$$RP^{E}(h,t) = RC^{E}(h,t) \times q^{R,E} \tag{11}$$

$$RP^{R}(h,t) = RC^{R}(h,t) \times q^{R,R} \tag{12}$$

The shiftable appliances constraint which shows the time limitation of their performance is given as follows:

$$\sum_{t=\tau s}^{\tau e} d(t,h,ty) = \tau w \tag{13}$$

$$HDA(t,h,ty) = \sum_{\tau w} d(t,h,ty) \times HDA^{n}(h,ty) \tag{14}$$

For shiftable load scheduling, τs and τe represent the desired start and end time of the shiftable appliances working period, and τw is the required time that they need to perform their applications. Also, it is assumed that the working period of the shiftable appliances cannot be interrupted.

Demand response programs

In this paper, an incentive payment oriented demand response scheme is considered for MG short term operational planning. In the assumed load management program, three types of incentive-based demand response programs are considered as follows:

- *Demand bidding/buyback programs* – Demand bidding/buyback programs encourage heavy consumers (like industrial and commercial loads) to offer load reductions at a price at which they are willing to be curtailed.
- *Ancillary Services Market Programs* – In this type of program customers can bid load curtailment as reserve capacity for the system. If their bids are accepted, they are paid at the reserve price for their involvement and for remaining in standby. If their load curtailments are needed, they are called by the MGO, and can be also paid at their accepted offer price for load reduction.
- *Direct load control* – Direct load control (DLC) programs refer to programs in which a utility or system operator remotely shuts down or cycles a customer's electrical equipment on short notice. In the proposed approach, the MGO is able to control some appliance of household directly. For example, it may control lighting, thermal comfort equipment (i.e., heating, ventilating, and air conditioning), refrigerators, and pumps.

More details about these programs are available in [34].

Wind and solar generation modeling

It is assumed that wind turbines and PV units are installed in the MG. As the wind and solar have a probabilistic nature, the output power of these units is intermittent. To model the uncertainties related to wind and PV generation, two different probability density functions are implemented.

Wind generation modeling

The Rayleigh probability density function (PDF) is regularly used as a proper expression model of wind speed behavior in each forecasted period [35]. Rayleigh PDF is a special case of Weibull PDF in which the shape index is equal to 2.

$$f_w(v) = (k_1/c)(v/c)^{(k_1-1)} e^{-(v/c)^{k_1}} \tag{15}$$

where k_1 and c are, respectively, shape factor (dimensionless) and scale factor (it shares the unit of v). The probability of the wind speed state v during any specific hour is calculated using (16):

$$\rho(v) = \int_{v_1}^{v_2} f_w(v)dv \tag{16}$$

where v_1 and v_1 are the wind speeds limits of state v.

The output power of the wind turbine is calculated using the wind turbine power curve parameters as described by Eq. (17). In order to simplify the analysis, the average value of each interval (v_a) is used to calculate the output power in that interval:

$$P_w(v) = \begin{cases} 0, & 0 \leqslant v_a \leqslant v_{ci} \\ P_{rated} \times \frac{(v_a - v_{ci})}{(v_r - v_{ci})}, & v_{ci} \leqslant v_a \leqslant v_r \\ P_{rated}\, v_r \leqslant v_a \leqslant v_{co} & \\ 0, & v_{co} \leqslant v_a \end{cases} \tag{17}$$

where v_{ci}, v_r and v_{co} are the cut-in speed, rated speed and cut-off speed of the wind turbine, respectively.

Solar generation modeling

The output of PV unit mainly depends on irradiance. The distribution of hourly irradiance at a particular location usually follows a bimodal distribution, which can be seen as a linear combination of two unimodal distribution functions [36,37]. A Beta PDF ($f_b(\phi)$) is utilized for each unimodal [36], as set out in the following:

$$f_b(\phi) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times \phi^{(\alpha-1)} \times (1-\phi)^{(\beta-1)} & for\ \ 0 \leqslant \phi \leqslant 1, \alpha \geqslant 0, \beta \geqslant 0 \\ 0 & otherwise \end{cases} \tag{18}$$

To calculate the parameters of the Beta distribution function (α, β), the mean (μ) and standard deviation (σ) of the random variable are utilized as follows:

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1\right) \tag{19}$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \tag{20}$$

The probability of the solar irradiance state ($\rho(\phi)$) during any specific hour can be calculated as follows:

$$\rho(\phi) = \int_{\emptyset_1}^{\emptyset_2} f_b(\phi).d\phi \tag{21}$$

where $\varnothing_1$ and $\varnothing_2$ are the solar irradiance limits of state $\varnothing$.

Given the irradiance distribution and irradiance-to-power conversion function, the PV power distribution can be obtained. The irradiance-to-power conversion function used in this paper is similar to that used in [38]:

$$P_{pv}(\phi) = \eta^{pv} \times S^{pv} \times \phi \tag{22}$$

Scenario generation

A 5-interval wind speed and solar irradiance discrete probability distribution functions are considered for wind and PV generation fluctuation at each hour, respectively. In order to combine different states of wind and PV fluctuations in each period, a scenario tree technique is used [39]. It is supposed that the wind speed and the solar irradiance have no correlation and each scenario consists of two different states of wind and PV generations. Each scenario is assigned a weight $\pi_s = \rho(v) \times \rho(\phi)$ that reflects its possibility of occurrence in the future.

Stochastic scheduling formulation

To model the wind and PV power generations' uncertainties within the MG energy and reserve scheduling, a two-stage stochastic programming framework is developed. In the stochastic method, all plausible states of wind and solar generation in each hour are modeled by generating different scenarios. The scheduling of energy resources is carried out for all scenarios in order to analyze the changes in power requirements while each of scenarios happens. The output result of this scheduling method is defined as the optimum solution that has the minimum operational cost if each of scenarios occurs in real time. So, the output result variables are different from scenario variables and are located in the first stage of objective function. The difference between output variables and scenario variables of DGs and responsive loads are defined as reserve. In other words, reserve is used in order to match the power shortage while renewable power generations suddenly decrease.

The involuntarily load shedding is used in the stochastic method to prevent committing more reserve in some scenarios with low probability. The amount of shed load in each scenario multiplied by the probability of scenario occurrence represents the Expected Energy Not Served (EENS). The Value of Lost Load (VOLL) rate is used in order to calculate the load shedding cost in each scenario; it is defined as the value that an average consumer loses from an unsupplied kW h of energy [15]. Within the optimization procedure, a tradeoff between reserve and involuntary load shedding costs is carried out in order to allocate optimum amount of reserve. For example, allocating more reserve for a scenario with very low probability in which high amount of wind or solar power shortage will occur is not necessary.

The total expected cost (*Ecost*) of the MG represents the cost objective function of the stochastic method that should be minimized [16,40]. The cost objective function has two parts: the first one is the sum of contracting energy and reserve costs (output variables) which should be paid to the market operator, DG owners and to customers participating in DR programs, while the second part represents the operational cost associated to each scenario (scenario variables). Set $s = 1,\ldots,S$ shows the scenarios number; so, scenario variables are distinguishable from output variable by using index s.

The non-ideal states of renewable power generation are taken into account within the energy and reserve scheduling by considering different scenarios in the carried out analysis. For example, if we consider a non-ideal case in which a wind or solar power suddenly reduces, the operator will use the scheduled reserve in order to compensate the renewable power shortage and maintain the balance between electricity generation and consumption. In other words, in the case that wind and solar power are different from the predicted values, a reserve capacity is scheduled by using the proposed method in order to compensate the sudden shortage of the renewable generation.

Objective function definition

The first part of cost objective function takes into account the total contracting energy and reserve costs ($CF1$) and represents the payment costs of electricity and reserve in the total scheduling horizon as follows:

$$\begin{aligned} CF1 = \sum_{t=1}^{T} \Bigg[& P_{grid}(t) \times Ta_g^E(t) + \sum_{j=1}^{J} \{ C_{DG}(j,t) + R_{DG}(j,t) \times C_{DGj}^R(j,t) \\ & + SU(j,t) \} + \sum_i IP^E(i,t) + IP^R(i,t) + \sum_b CP^E(b,t) + CP^R(b,t) \\ & + \sum_h RP^E(h,t) + RP^R(h,t) \Bigg] \end{aligned} \tag{23}$$

The second part of cost objective function takes into account the operational costs associated to each scenario ($CF2(s)$) and represents the cost associated to actual deployment of reserve in each scenario as follows:

$$\begin{aligned} CF2(s) = \sum_{t=1}^{T} \Bigg[& \sum_{j=1}^{J} Cs_{DG}(j,t,s) + \sum_{b=1}^{B} CP^s(b,t,s) + \sum_{i=1}^{I} IP^s(i,t,s) \\ & + \sum_{h=1}^{H} RP^s(h,t,s) + ENS(s,t) \times VOLL(t) \Bigg] \end{aligned} \tag{24}$$

To implement a linear programming approach, a linear cost function of DG is considered. The cost function $C_{DG}(j,t)$ is given by:

$$C_{DG}(j,t) = a_j \times u(j,t) + b_j \times P_{DG}(j,t) \tag{25}$$

where a_j and b_j are, respectively, cost coefficients of DG j. Accordingly, the DG cost in each scenario ($Cs_{DG}(j,t,s)$) is calculated as follows:

$$Cs_{DG}(j,t,s) = a_j \times us(j,t,s) + b_j \times Ps_{DG}(j,t,s) \tag{26}$$

The cost objective function of the stochastic energy and reserve scheduling represents the total expected cost (*Ecost*) calculated as follows:

Minimize,

$$Ecost = CF1 + \sum_{s=1}^{S} \pi(s) \times CF2(s) \tag{27}$$

where $\pi(s)$ is the probability of scenario s.

Constraints

The constraints of the stochastic optimization method are described below:

Load balance

$$\begin{aligned} & P_{grid}(t) + \sum_{j=1}^{J} P_{DG}(j,t) + \sum_{w=1}^{W} Po_w(t) + \sum_{pv=1}^{PV} Po_{pv}(t) + \eta^+ \times P_B^+(t) \\ & - P_B^-(t) \\ & = P_L(t) + Loss(t) - \sum_i IC^E(i,t) - \sum_h RC^E(h,t) \\ & \quad - \sum_b CC^E(b,t) \ \forall\ t \end{aligned} \tag{28}$$

The energy balance at each scenario should also be satisfied.

$$P_{grid}(t) + \sum_{j=1}^{J} Ps_{DG}(j,t,s) + \sum_{w=1}^{W} P_w^s(s,t) + \sum_{pv=1}^{PV} P_{pv}^s(s,t) + \eta^+ \times P_B^+(t) - P_B^-(t) = P_L(t) + Loss(s,t) - \sum_i IC^s(i,t,s) - \sum_b CC^s(b,t,s) - \sum_h RC^E(h,t,s) - ENS(s,t) \quad \forall\, t,s \tag{29}$$

where $P_w^s(s,t)$ and $P_{pv}^s(s,t)$ represent, respectively, the output power of wind turbine w and of PV system pv in period t and scenario s .

Demand response participants' constraints

The scheduled reserves offered by Industrial ($IC^R(t)$), commercial ($CC^R(t)$) and residential ($RC^R(t)$) customers at each hour are defined as the additional load demand reduction of each customer in each scenario if compared to its scheduled load demand reduction. The selection of the maximum value guarantees that the scheduled load reserve can cover load reduction's requirement in all scenarios. In other words, the reserve provided by a customer is the largest amount of load reduction deviation in all possible scenarios away from the scheduled ones.

$$IC^R(i,t) \geqslant IC^s(i,t,s) - IC^E(i,t) \quad \forall\, s,i,t \tag{30}$$

$$CC^R(b,t) \geqslant CC^s(b,t,s) - CC^E(b,t) \quad \forall\, s,b,t \tag{31}$$

$$RC^R(h,t) \geqslant RC^s(h,t,s) - RC^E(h,t) \quad \forall\, s,h,t \tag{32}$$

The reactive power reduction of each load in the demand response program is considered proportional to the active power reduction according to the power factor of the considered load.

Non-renewable DG power and reserve constraints

The non-renewable distributed generation units have a maximum and minimum generating capacity beyond which it is not feasible to generate due to technical reasons. Generating limits are specified as upper and lower limits for the power outputs.

$$P_{DG}(j,t) + R_{DG}(j,t) \leqslant P_{DGj}^{max}.u(j,t) \quad \forall\, j,t \tag{33}$$

$$P_{DG}(j,t) \geqslant P_{DGj}^{min}.u(j,t) \quad \forall\, j,t \tag{34}$$

The start up cost ($SU(j,t)$) of DG units is calculated as follows:

$$SU(j,t) \geqslant Sc_j \times (u(j,t) - u(j,t-1)) \tag{35}$$

$$SU(j,t) \geqslant 0 \tag{36}$$

The spinning reserves ($R_{DG}(j,t)$) provided by DGs is calculated as follows:

$$R_{DG}(j,t) \geqslant Ps_{DG}(j,t,s) - P_{DG}(j,t) \quad \forall\, j,t,s \tag{37}$$

Regarding the Eq. (37), the DG power output deviation in each scenario (Ps_{DG}) if compared to the scheduled one (P_{DG}) is considered as the DG reserve (R_{DG}).

Battery charge and discharge constraints

The battery used in the MG cannot charge and discharge arbitrary. The following constraint should be considered for the scheduling program of the battery:

$$SOC(t) = SOC(t-1) + \eta^- \times P_B^-(t) - P_B^+ \tag{38}$$

$$SOC_{Min} \leqslant SOC(t) \leqslant SOC_{Max} \tag{39}$$

Also the charge and discharge limit should be considered as follows:

$$P_B^-(t) \leqslant P_{B\_Max}^- \tag{40}$$

$$P_B^+(t) \leqslant P_{B\_Max}^+ \tag{41}$$

$$X(t) + Y(t) \leq 1; X,Y \in \{0,1\} \tag{42}$$

Power flow constraints

$$P_{inj}(n,t) = \sum_{m=1}^{N} |V(n,t)||V(m,t)||Y_{n,m}| \cos(\delta(m,t) - \delta(n,t) + \theta_{n,m}) \quad \forall\, n,t \tag{43}$$

$$Q_{inj}(n,t) = -\sum_{m=1}^{N} |V(n,t)||V(m,t)||Y_{n,m}| \sin(\delta(m,t) - \delta(n,t) + \theta_{n,m}) \quad \forall\, n,t \tag{44}$$

The other network operation constraints are as follows:

$$|S(n,m,t)| \leqslant S_{n,m}^{max} \tag{45}$$

$$V_n^{min} \leqslant V(n,t) \leqslant V_n^{max} \tag{46}$$

$$P_{sub}(t) \leqslant P_{sub}^{max} \tag{47}$$

where $|S(n,m,t)|$ is the apparent power flow from node n to m; $S_{n,m}^{max}$ is the capacity of the line/cable between node n and node m; V_n^{max} and V_n^{min} are maximum and minimum voltage magnitude at node n, respectively; $P_{sub}(t)$ is the power output from the distribution transformer.

Computation technique

Solving the proposed mixed integer nonlinear model is very time consuming with available commercial solvers and in some cases the problem is not converged. In order to make the proposed model applicable for large MG with large number of consumers, and overcome the difficulties related to solving nonlinear optimization problems with binary variables, a fast and robust optimization technique known as Benders decomposition is implemented in this paper [41].

The basic idea behind this method is to decompose the problem into two simpler parts: the first part, called master problem, solves a relaxed version of the problem and get values for a subset of the variables. The second part, called sub-problem (or auxiliary problem), receives the values for the remaining variables while keeping the first ones fixed, and uses these to generate *benders cut* for the master problem. The master and auxiliary problems are solved iteratively until no more cuts can be generated. The combination of the variables found in the last master and sub-problem iteration is the solution to the original formulation [43].

In the proposed model, the Benders technique divides the original problem into a mixed integer linear programming (MILP) master problem (Eqs. (23)–(42)) and a nonlinear programming (NLP) sub-problem (Eqs. (43)–(47)). The master problem consists of 24-h stochastic energy and reserve scheduling problem which are solved by using the mixed-integer linear programming (MILP) solver CPLEX [43]. The sub-problem is an hourly radial MG power flow with some fixed variables received from the master problem solution which is solved using non-linear programming (NLP) solver CONOPT [44]. Both the master and the sub-problem are modeled in GAMS on a Pentium IV, 2.6 GHz processor with 4 GB of RAM. More details on benders decomposition and its features are available in [45] and its implementation in optimal power flow problem is described in [46].

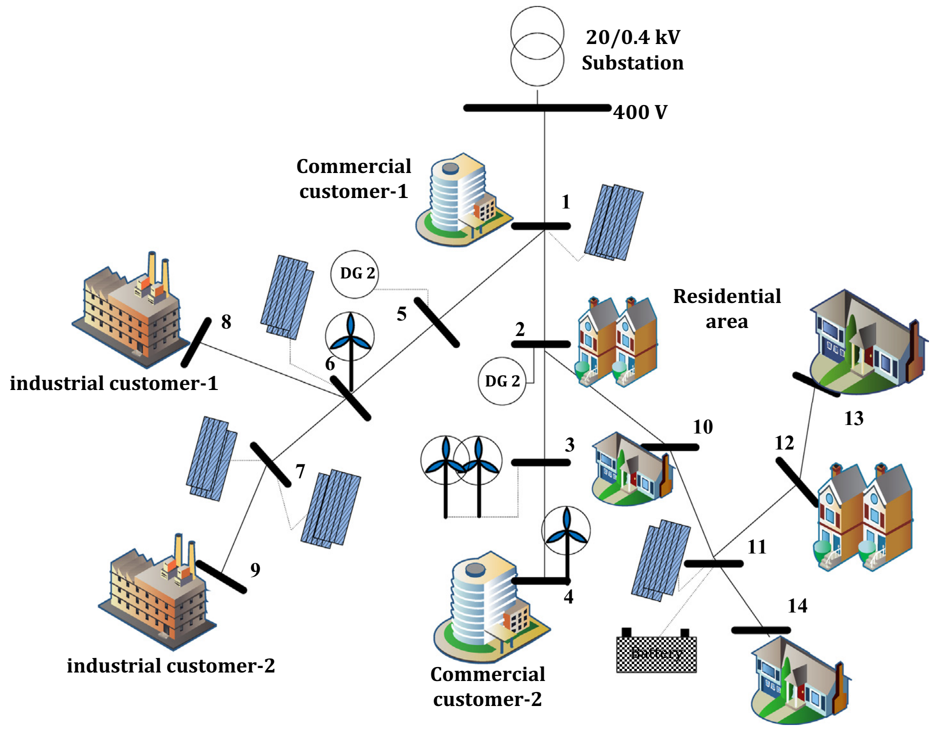

Fig. 3. 14-Bus microgrid test system.

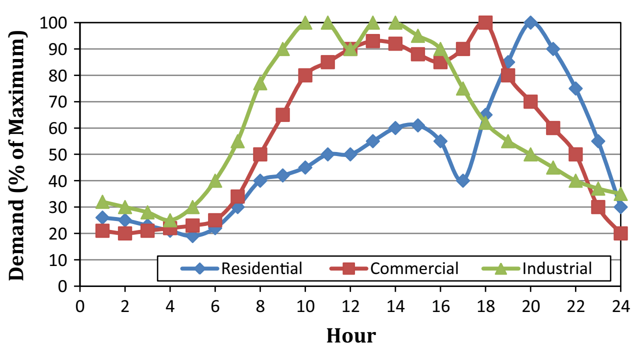

Fig. 4. Daily load curves for the three load types of The MG.

Case study

The proposed model was tested on a typical MG, in particular a 14-bus low voltage distribution test network is considered [47]. This test system is depicted in Fig 3. Three types of customers are considered in the MG: one hundred of residential customers, two commercial and two medium industrial customers. Aggregated daily load curves for the three load types are shown in Fig. 4 [48]. The maximum electricity demands of the aggregated residential, commercial and industrial customers are 200 kW, 100 kW and 300 kW, respectively. A variety of Distributed Energy Resources (DERs), such as two diesel generators, four directly coupled wind turbine (WT), and ten photovoltaic (PV) arrays are installed in the MG. It is assumed that all DGs produce active power at a unity power factor. The technical aspects of two diesel generators are shown in Table 1. The spinning reserve of DGs are priced at a rate equal to 20% of their cost of the energy production.

The energy storage system consists of a battery with a capacity of 30 kW which charging and discharging ramp rate limits for each hour equal to 10 kW and 20 kW, respectively. Four wind turbines are installed in the test system, they are of the same type: 30 kW power rated with cut-in speed of 3 m/s, nominal speed of 12 m/s, and cut-out speed of 25 m/s. Other specifications of the wind turbines are given in [49]. Ten 10 kW PV systems are installed in the test system: each of them is composed of 40 × 250 W solar panels with η = 18.6% and S^{PV} = 40 m^2 [50]. The average hourly wind speed is shown in Fig. 5, where $k_1 = 2$ and $c = v_{mean}/0.9$ m/s. The mean (μ) and standard deviation (σ) of the hourly solar irradiance are taken from [51] and shown in Table 2. The VOLL that is needed to estimate the social cost caused by interruptions is taken as 1 \$/kW h [52]. The hourly energy price of Ontario electricity market on Wednesday 23 January 2013 [53] has been assumed as shown in Table 3. The industrial and commercial customers' price and amount of offers for load reduction are presented in Tables 4 and 5, respectively. It is assumed that fifty percent of residential customers are willing to participate in DR programs during the scheduling horizon. In this case study, it has been assumed that each house has a demand curtailment capability of 500 W. Also, the

Table 1
Technical and economical features of diesel generators.

Unit	Cost coefficient			Technical constraints	
	a_j (\$)	b_j (\$/kW h)	Startup (\$)	P_{min} (kW)	P_{max} (kW)
DG1	0.5	0.053	0.15	30	300
DG2	0.8	0.068	0.21	40	400

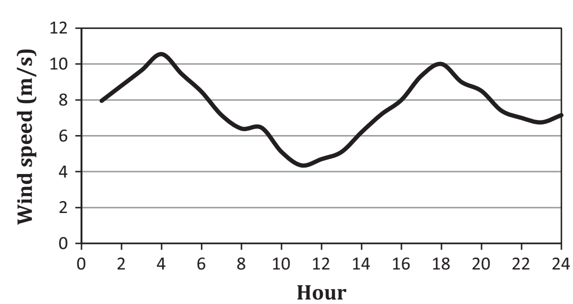

Fig. 5. Hourly mean wind speed.

Table 2
Mean and standard deviation of solar irradiance.

Hour	μ (kW/m^2)	σ (kW/m^2)	Hour	μ (kW/m^2)	σ (kW/m^2)
6	0.019	0.035	13	0.648	0.282
7	0.096	0.110	14	0.590	0.265
8	0.222	0.182	15	0.477	0.237
9	0.381	0.217	16	0.338	0.204
10	0.511	0.253	17	0.190	0.163
11	0.610	0.273	18	0.080	0.098
12	0.657	0.284	19	0.017	0.032

Table 3
Hourly price of open market.

t	1	2	3	4	5	6
$/MW h	47.47	31.64	31.65	32.60	40.78	38.64
t	7	8	9	10	11	12
$/MW h	158.95	384.14	67.27	52.29	44.59	108.49
t	13	14	15	16	17	18
$/MW h	60.64	40.88	28.50	38.75	35.55	112.42
t	19	20	21	22	23	24
$/MW h	575.58	87.72	35.06	47.18	61.27	33.90

Table 4
Price-quantity offer package for industrial customers (IC).

	Quantity (kW) Price (cent/kW h)			
IC1	0–5 7	5–10 15	10–50 29	50–70 41
IC2	0–5 5	5–20 7.5	20–30 31	30–60 49

residential customers participating in a DR program have a dishwasher and a washer dryer as shiftable appliances. The power consumption of the dishwasher and the washer/dryer are assumed to be 700 and 1200 W, respectively [53,54]. The dishwasher works two times during each day for washing launch in the range 13:00–18:00 and dinner dishes in the range 19:00–23:00, while each washing procedure needs one hour to wash dishes. The washer/dryer has been scheduled by customers to work in the range 17:00–24:00.

In order to analyze the effects of demand side participation in the MG energy and reserve scheduling, the proposed model is tested in the following two difference cases:

- Case 1: without considering DR programs.
- Case 2: considering DR programs.

Table 6 compares the operational cost of the MG with and without considering DR programs. The costs of the main grid scheduled energy, as well as of DGs scheduled energy and reserve, are compared in these two cases. As shown in Table 6, this comparison shows that the proposed model deploying DR program allows obtaining lower total operation costs.

The scheduled energy and reserve in the case without considering DR programs are shown in Figs. 6 and 7, respectively. In this case, all the required reserves are arranged by diesel generator units. So, a part of the Diesel generators capacity should be kept for covering renewable generation uncertainty. Also, for arranging spinning reserve at some hours, the Diesel generators are forced to be turned on at their minimum power output in order to be ready (stand-by) to deliver spinning reserve.

In case 2, the operational planning is performed by considering demand response programs. The energy scheduling and demand participation are shown in Figs. 8 and 9, respectively. As customers participate in energy and reserve scheduling, the grid and diesel generators scheduled power changed. The demand participation in reserve scheduling is shown in Fig. 10.

As shown in Fig. 9, the demand response during the hours with high energy price is higher than during low energy price hours. This means the MGO purchases load curtailment when the hourly electricity price is high. Comparing Figs. 6, 8 and 10, it can be observed that the reserve provided by customers is such that the diesel generators are not forced to be turned on during all the hours to provide the reserve.

The revenues of customers participating in DR programs are shown in Table 7. Each residential customer has, in fact, a dishwasher (700 W) and a washer/dryer (1200 W). The dishwasher is scheduled to work at hour 15:00 and 21:00 for lunch and dinner dishes, respectively. The washer dryer, is instead, scheduled to work at 21:00 and 22:00. Accordingly, the saved money for the dishwasher working in the scheduled periods is 1.68 and 8.82 cents for lunch and dinner, respectively, while for the washer/dryer is 24 cents. The total saved money during the 24-h period is therefore equal to 34 cent.

The battery charge/discharge scheduling is shown in Fig. 11. According to the hourly electricity price shown in Table 3, it's worth noting that the battery charging occurs during hours with lower electricity prices and the battery discharge occurs during hours with higher electricity prices. So, the battery charging and discharging scheduling also determines a decrease of the MG operation costs.

In order to evaluate the effect of uncertainty of renewable generations on reserve scheduling, a specific scenario in which wind and solar power shortages happen is analyzed. Let's consider the

Table 5
Commercial customers (CC) load reduction offer.

Hour	CC1		CC2	
	Maximum reduction (kW)	Price (cent/kW h)	Maximum reduction (kW)	Price (cent/kW h)
8	15	6	12	14
9	9	7	24	9
10	5	4	5	12
13	7	10	–	–
14	7	50	–	–
15	21	60	16	12
16	7	8.5	19	8
17	10	6	25	60
18	4	10	18	60
19	15	20	10	30
20	28	30	18	10
21	10	30	21	6
22	3	30	8	20
23	6	30	–	–

Table 6
Scheduling cost comparison in two cases: with and without DR.

Cost ($)	Main grid	Diesel generators		DR		Total
	Energy	Energy	Reserve	Energy reduction	Reserve	
Without DR	318.81	94.16	12.12	–	–	425.09
With DR	263.86	98.35	2.01	20.25	3.97	388.44

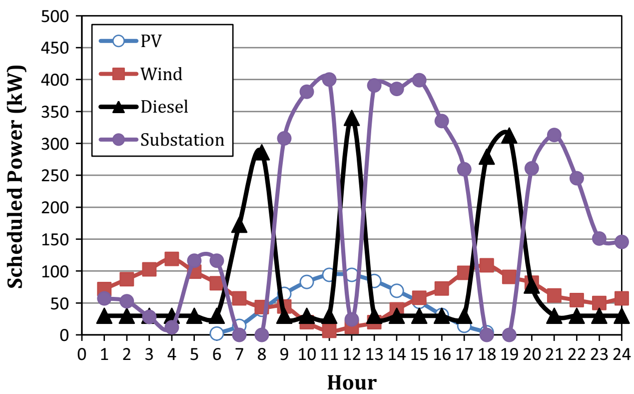

Fig. 6. Scheduled energy in case 1.

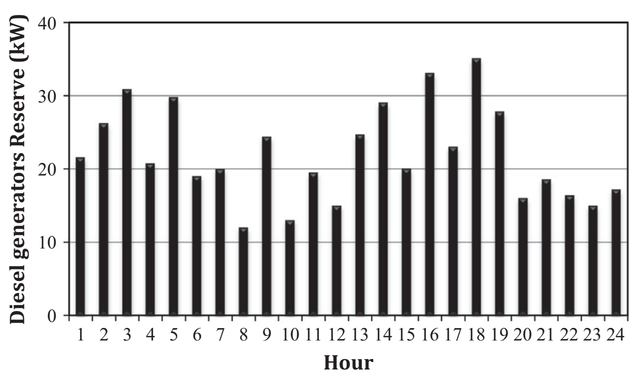

Fig. 7. Scheduled reserve in case 1.

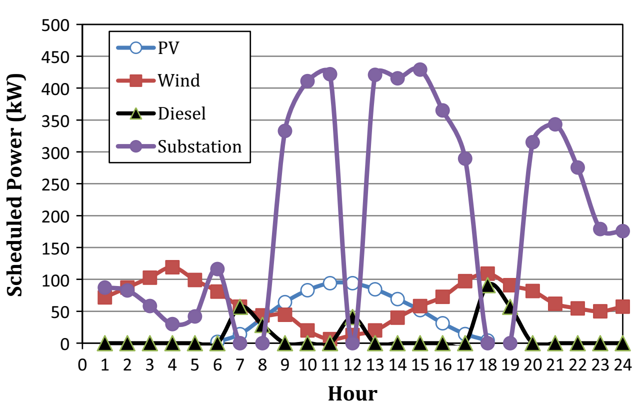

Fig. 8. Scheduled energy in case 2.

scheduling results at hour 14; the predicted values for wind and solar power in this period are 40 and 56 kW, respectively. According to Fig. 10, the total scheduled reserve for this period is 28 kW. In real time (e.g. hour 14), it is assumed that the wind and solar power suddenly changes and the available wind and solar power are 30 and 42 kW, respectively. In this case, the operator calls

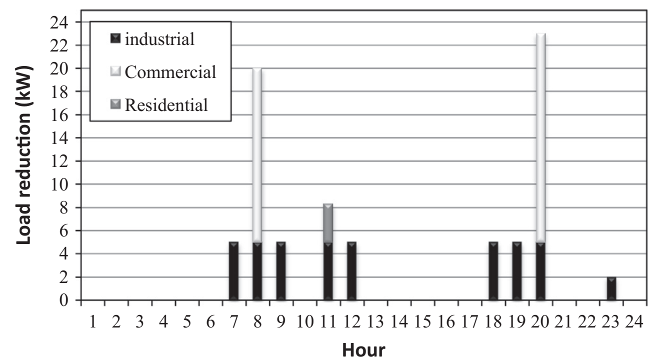

Fig. 9. Scheduled demand curtailment in case 2.

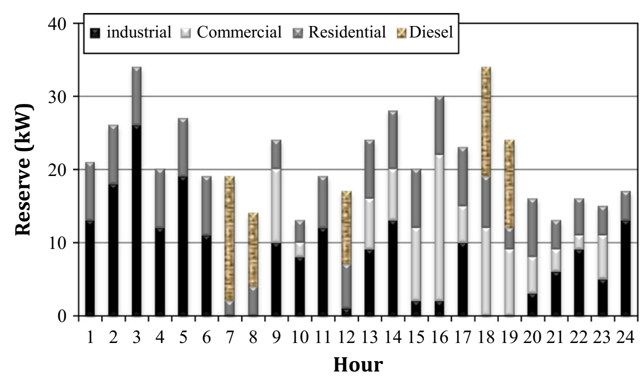

Fig. 10. Scheduled reserve in case 2.

Table 7
Customers revenue from participating in DR program.

Customers	Industrial	Commercial	Residential
Revenue ($)	10.97	6.94	5.13

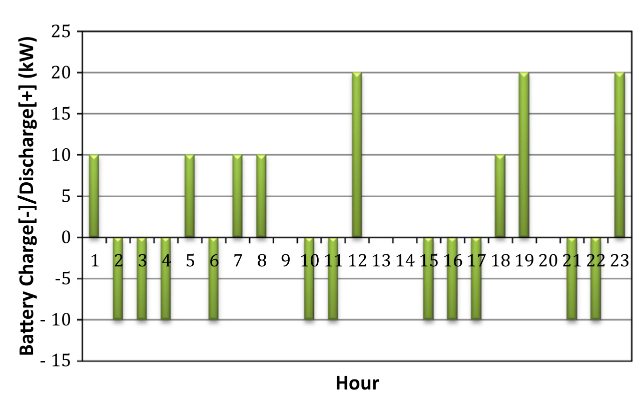

Fig. 11. Battery charge/discharge scheduling in case 2.

reserve providers to deliver the scheduled reserve. The renewable power shortage in this case is 24 kW that is compensated by 24 kW of the 28 kW scheduled reserve capacity.

Conclusions

In this paper, an energy and reserve scheduling method for a MG, using stochastic optimization was proposed. The approach allows different type of customers participating in both energy and reserve operational scheduling. Demand bidding/buyback programs, ancillary service market program and direct load control are considered as demand response programs. Also, the uncertainties of wind and solar generations have been modeled by related probability functions. The results show that customers' involvement in the energy and reserve scheduling reduces the total operational costs of the MG. Moreover, while the customers provide reserve, the diesel generator usage can be limited.

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