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Stochastic multi-objective operational planning of smart distribution systems considering demand response programs

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ABSTRACT

The development of smart grids offers new opportunities to improve the efficiency of operation of Distributed Energy Resources (DERs) by implementing an intelligent Distribution Management System (DMS). The DMS consists of application systems that are used to support the DERs management undertaken by a Distribution System Operator (DSO). In this paper, a conceptual model for a Demand Response Management System (DRMS), conceived as an application system of a DMS, is presented. Moreover, an optimization tool, able to consider the available DERs (conventional or renewable Distributed Generations (DGs) and demand response) is proposed. The optimization tool uses a stochastic multi-objective method in order to schedule DERs and aims at minimizing the total operational costs and emissions while considering the intermittent nature of wind and solar power as well as demand forecast errors. In order to facilitate small and medium loads participation in demand response programs, a Demand Response Provider (DRP) aggregates offers for load reduction. The proposed scheduling approach for DERs is tested on a 69-bus distribution test system over a 24-h period.

1. Introduction

Future distribution systems will face with a huge penetration of Distributed Energy Resources (DERs) that may effect on reliable and secure operation of the system and the intermittent nature of renewable generation may put at risk the system operation [1]. Efficient and robust DERs scheduling models are, therefore, necessary for future distribution system operation and control. In order to implement advanced scheduling of DERs for reliable and economic operation of future distribution systems, Advanced Metering Infrastructure (AMI) integrated with application systems represents an essential infrastructure [2–6]. Application systems refer to software systems responsible for monitoring, measurement and control of the electrical grid in order to ensure its reliability and availability as well as the energy management while guaranteeing balanced supply and demand [7–9]. As defined in IEC 61968, a Distribution Management System (DMS) consists of various distributed application components able to manage electrical distribution networks [10]. These capabilities include monitoring and control of equipment for power delivery, management processes to ensure system reliability, demand-side management, voltage management, outage management, automated mapping, work management and facilities management [10,11]. Application systems allow Distribution System Operators (DSOs) optimizing the use of Distributed Generation (DG) and enable customers to participate in various Demand Side Management (DSM) programs. Also, AMI system allows real-time communication between customers, service providers and utilities in order to send and receive useful energy and price information, as well as offer and command signals.

Demand Response (DR), known as an important DER, is a valuable resource for secure and economic operation of the power system. A survey of DR potentials and benefits in smart grids is presented in [12]. Innovative enabling technologies and systems, critical to enable the management of DR in a smart grid, are discussed also considering research projects and real industrial case studies.

In general, DR includes all planned electricity consumption pattern modifications by end-use customers that are intended to modify the timing and/or the level of their electricity consumption in response to incentive payments or to changes in the price signal over time. In order to evolve to successful practical implementations of all types of DR programs, distribution systems require new Information Technology (IT) systems [12–14] as well as application systems that manage and schedule all available DERs. Demand Response Management System (DRMS) is introduced as one of

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Nomenclature

Sets
t index of optimization periods, $t = 1,2,...,24$
i index of demand response providers, $i = 1,2,...,I$
ξ index of steps in load reduction offer, $\xi = 2,3,...,\Phi$
j index of non-renewable DGs, $j = 1,2,...,J$
s index of scenarios, $s = 1,2,...,S$
w index of wind turbines, $w = 1,2,...,W$
pv index of photovoltaic (PV) units, $pv = 1,2,...,\Theta$
n,m index of buses, $n,m = 1,2,...,N$
k index of objective functions, $k = 1,...,K$
z index of Pareto-optimal solutions, $z = 1,...,q_k$

Binary variables
$u(j, t)$ on/off status (1/0) of the non-renewable DG j in period t

Continuous variables
F_{cost} total expected cost
$F_{emission}$ total emissions
l_{ξ}^{i} accepted load reduction of DRP i in step ξ of the price-quantity offer package
$DR^{E}(i, t, s)$ total scheduled load reduction quantity prepared by DRP i in period t and scenario s
$C^{DR}(i, t, s)$ cost due for load reduction provided by DRP i in period t and scenario s
$DR^{R}(i, t)$ scheduled reserve provided by DRP i in period t
$RC^{DR}(i, t)$ cost due for reserve supply by DRP i in period t
$P_g(t)$ scheduled hourly power from the main grid in period t
$C_{DG}(j, t, s)$ hourly running cost of non-renewable DG j in period t and scenario s
$fc(j, t)$ hourly fixed running cost of non-renewable DG j in period t
$SU(j, t)$ start up cost of non-renewable DG j in period t
$ENS(n, t, s)$ amount of involuntarily load shedding at bus n in period t and scenario s
$P_{DG}(j, t, s)$ active output power of non-renewable DG j in period t and scenario s
$R_{DG}(j, t)$ scheduled spinning reserve provided by non-renewable DG j in period t
$V(n, t, s)$ voltage at bus n in period t and scenario s

Parameters
$D_{n,t,s}$ hourly demand at bus n in period t and scenario s
$P_{s,t}^{w}$ output power of wind turbine w in period t and scenario s
$P_{s,t}^{pv}$ output power of PV system pv in period t and scenario s
L_{Min}^{i} minimum quantity of load reduction offered by DRP i in period t
L_{Max}^{i} maximum quantity of load reduction offered by DRP i in period t
O_{ξ}^{i} price offer of DRP i for load reduction at step ξ
$q_{i,t}$ price offer of DPR i for providing reserve in period t
$E_{CO_2}^{grid,t}$ average emission rate of the main grid generation system in period t (kg/MWh)
$D_{CO_2}^{DG,j}$ emission rate of DG j (kg/MWh)
v wind speed (m/s)
si solar irradiance (kW/m^2)
Ω_t hourly electricity price of the open market
$RP_{j,t}$ reserve price of non-renewable DG j in period t
V_t Value of Lost Load (VOLL) in period t

Sets
$P_{DG,j}^{min}$ minimum output power limit of non-renewable DG j
$P_{DG,j}^{max}$ maximum output power limit of non-renewable DG j
Sc_j start-up cost of non-renewable DG j
$Y_{n,m}$ element (n, m) of the admittance matrix

these application systems within a DMS that supports DSO in order to manage DR programs and control DGs operations in a distribution system [15,16]. Future DMSs must be designed to support the integration of DERs into distribution networks. A significant number of works is contributing to the diversity of new features required for DMS and also evidencing challenges that they must face [17–19]. In [17], the management tools of conventional distribution systems have been compared with those of smart grid systems. In [18], conventional distribution automation has been compared with smart distribution management. In addition, distribution state estimation, Volt/Var control, and network reconfiguration have been presented in the paper as solutions for smart distribution application systems. In [19], algorithms for DMS have been presented in which load estimation, power flow, and optimal reconfiguration for loss minimization were taken into account. However, an application system for DR program management has not been presented in these works.

In [20] a conceptual design of an intelligent Supervisory Control and Data Acquisition (SCADA) has been proposed. The SCADA model is used to support the energy resource management undertaken by a DSO. DER management considers all the involved costs, power flows, and electricity prices, allowing the use of network reconfiguration and load curtailment. Direct load control (DLC) and locational marginal prices triggered events have been considered as DR programs. However, the intermittent nature of renewable generation as well as reserve scheduling were not taken into account in the model.

An intelligent on-line DSM system for peak load management in low-voltage distribution networks has been presented in [21]. The system uses low-cost controllers with low-bandwidth two-way communication installed in customers' premises and at distribution transformers in order to manage the peak load while maximizing customer satisfaction. Reserve scheduling as an ancillary service and incentive based DR were not taken into account in the model. An energy management system (EMS) aiming at optimizing the smart grid's operation has been proposed in [22]. The EMS behaves as a sort of aggregator of DERs allowing the SG participating in the open market. By integrating demand side management and active management schemes, it permits an enhanced exploitation of renewable energy sources and a reduction of the customers' energy consumption costs with both economic and environmental benefits.

A lot of good work has been historically done on DSM and DR programs [23–28]. The schemes can generally be classified into either dispatchable or non-dispatchable [16,23]. Non-dispatchable DR resource, often known as price-based DR, refers to some DR programs according to which the consumer consumption patterns are amended by different electricity prices over the time [24,25]. real time pricing (RTP) and time of use (TOU) are located in this category. As the customer decides whether and when to reduce consumption and the amount of consumer electricity usage changes cannot be exactly determined before the real time, this type of DR programs are called non-dispatchable and the operator cannot consider them in the day-ahead energy and reserve scheduling. Dispatchable DR resource, known as incentive-based DR, refers to planned changes in consumption that the customer agrees to make in response to requests from the electric utility or service provides [26–28]. The focus of the method proposed in this paper is on dispatchable DR programs.

In order to make an efficient use of DERs, the scheduling of DG units should be integrated with DR programs. In [29,30], it has been illustrated that the use of DG can be, in some cases, more advantageous than DSM contracts. Accordingly, in order to operate the distribution network with the maximum reliability and minimum cost, DGs scheduling and DR management should be simultaneously taken into account in DRMSs.

As air pollution and global warming have been recognized as one of the main critical environmental issues, the electrical industry should also contribute to emissions reduction [31–33]. Thus, environmental concerns that arise due to the operation of fossil fuel fired electric generators change the classical economic electricity operational planning problem into a multi-objective economic/emission operational planning problem [34].

According to the presented literature review, it is worth noting that previous works paid attention to the energy reduction capability of DR programs without considering the option to use DR programs in reserve scheduling for distribution systems. In addition, the integration of intermittent renewable generation and DR has not been considered in most of previous works.

Nevertheless, most of previous works were carried out from the perspective of price elasticity feature of electricity consumption. Even if some research works have tried to explore the implementation pattern and interaction mechanism of dispatchable DR programs, DR participation in reserve scheduling was not considered.

This paper presents a new conceptual design of an intelligent DRMS integrated with an AMI system in order to support DERs management in the environment of future distribution systems. A smart DRMS gives the DSO access to relevant data concerning distribution network situation as well as DGs and DR program states. Also, a new method for energy and reserve scheduling in distribution networks is proposed as one of DRMS applications. The proposed method considers DR programs in both of energy and reserve scheduling as well as renewable generation uncertainty.

The rest of the paper is organized as follows: after the initial introductory section, Section 2 deals with the architecture of the proposed DRMS. In Section 3, the probabilistic models of wind, solar and demand are presented. Also, the multi-objective DERs scheduling is formulated. Section 4 presents a case study using a 69 bus distribution network. Section 5 presents the most important conclusions of the presented work.

2. Proposed system architecture

In order to achieve an optimal network operation, it is required a continuous real time monitoring, control and management of DERs by means of a smart DMS [35,36]. The enrollment of customers participating in different types of DR programs and the announcement by DSO of the starting and ending times of a DR event require a two-way communication system. In this section the architecture of an Advanced Metering Infrastructure (AMI) with DRMS is presented.

2.1. Advanced metering infrastructure

In order to achieve the goals of the DMS, it is essential to enable a two-way exchange of a variety of real-time information between DSO and consumers by applying information technology. In addition, the accurate measurement of the energy absorbed by customers while they participate in a specific DR program is required in order to calculate their payments. So, the smart metering system architecture of a real pilot project is considered for the proposed distribution network configuration [37,38] as shown in Fig. 1. It 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 General Packet Radio Service (GPRS).
- *Data concentrators* (DC) installed in proximity of 20 kV/400 V distribution 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* (MDMS) 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 DSO and application systems.

2.2. Demand Response Management System

DRMS is one of the application systems within DMS. The simplified conceptual model of DRMS is shown in Fig. 2. DRMS makes a decision for both day-ahead and real-time scheduling and management of DERs. The focus of this paper is on day-ahead scheduling. In the proposed model, the DSO is responsible for DMS and has a supervisory control and monitoring on the optimization procedure. The proposed method is carried out by DRMS in DMS. DSO monitors the optimization procedure and is the final decision maker. Moreover, the DSO is responsible for both energy and reserve scheduling in the distribution system. During the day-ahead DRMS simultaneously schedules energy and reserve of the distribution system. DGs and DRP offer the price for providing reserve to the DSO.

In day-ahead DERs scheduling, firstly, DRMS receives enrolment information of DR participants from Customer Information System (CIS). Customers who are willing to participate in a DR program have filled out the participation forms by cell phone program or an available Internet portal. Also, DRMS accesses to DGs bid, forecasted load, wind speed and solar radiation data for the following 24 h. Then, the DERs scheduling is carried out by DRMS and the output results for load demand reduction and DGs output power are determined. Moreover, the reserve amount and providers are determined. Then, DRMS sends the results to MDM system in order to inform the customers and DGs' owners.

DRMS also is responsible for payment calculation. So, after the scheduling period, the exact consumption and generation data are received from MDMS and the amount of customers load curtailments and DGs power generation are calculated by MDMS. The payment calculation result is sent to the billing system in order to register customers' bills. In order to evaluate each DR event, DRMS has a database in which the behavior of each DR participant is recorded. Historical data in the database can also be used for offline analysis.

3. The multi-objective energy and reserve scheduling

In the proposed model, DERs scheduling in distribution networks are managed by the DSO [39,40]. In addition, the DSO uses DMS software and application systems as well as AMI system in order to manage and control the distribution network [22]. In this section, day-ahead energy and reserve scheduling of distribution system as an application of DRMS is presented.

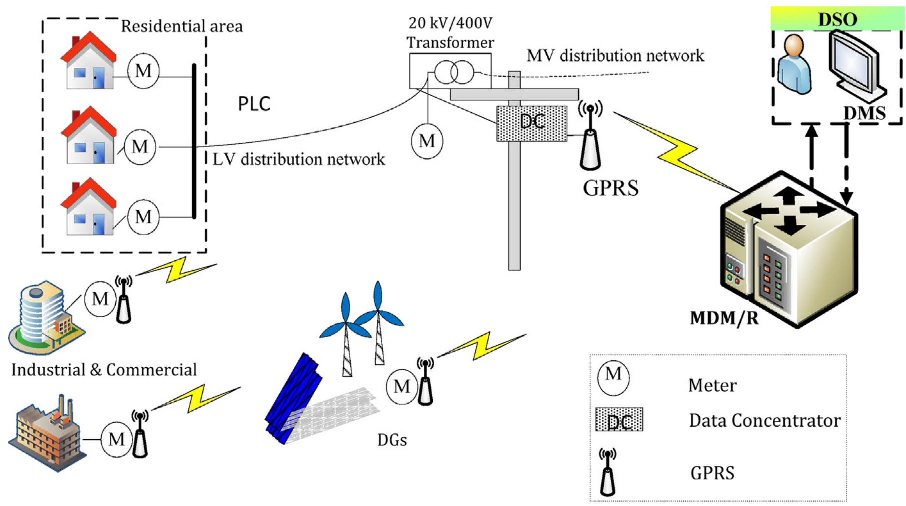

Fig. 1. Advanced metering architecture.

The assumptions used in the proposed method are the following ones:

- wind and solar producers are not considered competitive agents and their generation should be totally purchased [41].
- the wind speed and solar radiation forecasts are received from the nearest weather broadcast service.
- reserve capacity should be provided by available DERs such as DGs and DR resources in the distribution network.
- DGs' owners submit their energy and reserve bids as well as technical constraints of their DGs to the DSO for participating in the day-ahead energy and reserve scheduling.

In the proposed stochastic model, the wind and solar intermittent nature as well as electricity demand forecast error are modeled by scenarios. A different probability Density Function (PDF) is used to model the uncertainty of wind, solar and demand that are detailed as follows.

3.1. Wind generation modeling

The Rayleigh PDF is regularly used as a proper expression model of wind speed behavior [42]. Rayleigh PDF is a special case of Weibull PDF in which the shape index is equal to 2.

$$f(v) = \left(\frac{2v}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{1}$$

where (v), c and v are Rayleigh PDF, scale index and wind speed, respectively. If the mean value of the wind speed (v_m) for a site is known, then the scaling index c can be calculated as in (2) and (3):

$$v_m \int_0^{\infty} vf(v)dv = \int_0^{\infty} \left(\frac{2v^2}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^2\right] dv = \frac{\sqrt{\pi}}{2}c \tag{2}$$

$$c \simeq 1.128v_m \tag{3}$$

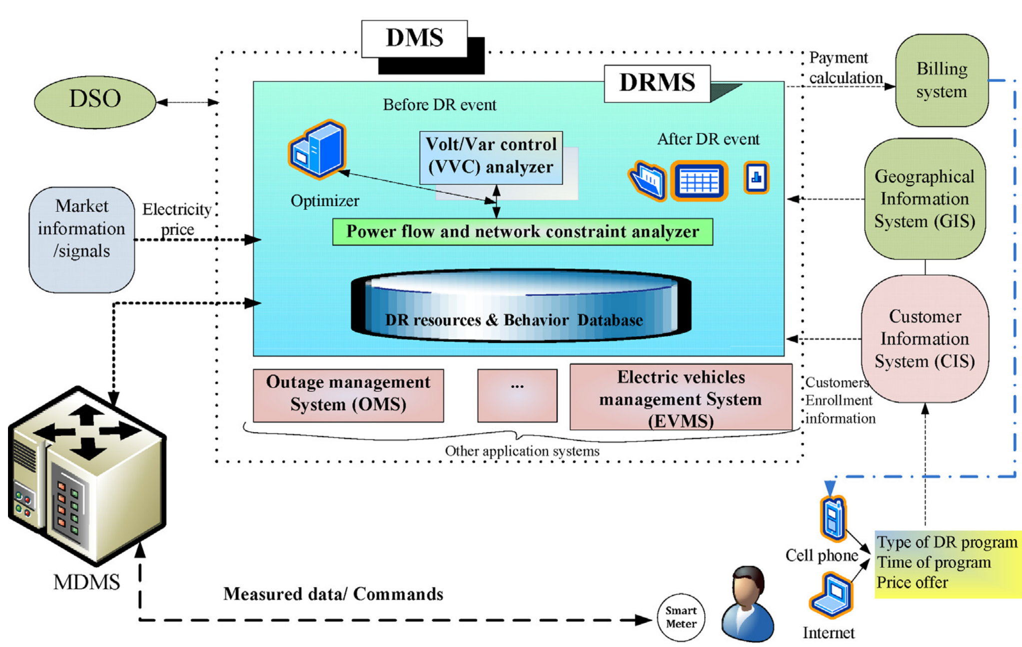

Fig. 2. 41 DRMS – information and decision flow.

A 5-interval wind speed probability distribution function is selected to model hourly wind speed uncertainty. The probability of each interval (P_ϖ) is calculated using Eq. (4):

$$p_\varpi \int_{v_{\varpi 1}}^{v_{\varpi 2}} f(v)dv \tag{4}$$

where $v_{\varpi 1}$ and $v_{\varpi 2}$ are the speed limits of interval ϖ. The output power of the wind turbine, corresponding to each interval, is calculated by using the wind turbine power curve parameters as described by Eq. (5). In order to simplify the analysis, the average value of each interval ($v_{a\varpi}$) is used to calculate the output power for each interval.

$$P_\varpi(v) = \begin{cases} 0, & 0 \le v_{a\varpi} \le v_{ci} \\ P_{rated} \times \dfrac{(v_{a\varpi} - v_{ci})}{(v_r - v_{ci})}, & v_{ci} \le v_{a\varpi} \le v_r \\ P_{rated} & v_r \le v_{a\varpi} \le v_{co} \\ 0, & v_{co} \le v_{a\varpi} \end{cases} \tag{5}$$

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

3.2. Solar generation modeling

The output of Photovoltaic (PV) system mainly depends on irradiance. The distribution of hourly irradiance at a particular location usually follows a bimodal distribution [43,44], which can be seen as a linear combination of two unimodal distribution functions [45]. A Beta PDF is utilized for each unimodal [44,46], as set out in the following:

$$f_b(si) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times si^{(\alpha-1)} \times (1-si)^{(\beta-1)} & \text{for} \quad 0 \le si \le 1, \alpha \ge 0, \beta \ge 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where si represents the solar irradiance (kW/m^2). In order 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:

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1 \right) \tag{7}$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \tag{8}$$

A 5-interval solar irradiance probability distribution function is used to generate solar irradiance states at each hour. 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 [47]:

$$P_{pv}(si) = \eta^{pv} \times S^{pv} \times si \tag{9}$$

where $P_{pv}(si)$ represents PV output power (kW) for irradiance si; η^{pv} and S^{pv} are the efficiency (%) and total area (m^2) of PV system, respectively.

3.3. Load modeling

The normality assumption for the demand forecast error is mainly used in the literature [48]. In order to generate a limited number of demand states during each hour, it is generally sampled from the distribution curve. In the proposed method, the error associated to load demand is assumed to be normally distributed and the weights ρ_d are given by the area under the curve between the lower and upper limits of each interval ε.

$$\rho = \frac{1}{\sigma_d\sqrt{2\pi}} \int_{l_\varepsilon}^{u_\varepsilon} e^{-(x-d_f)^2/2\sigma_d^2} d_x \tag{10}$$

where u_ε and l_ε are, respectively, the upper and lower limits of load demand in each interval; d_f and σ_d are the net forecast demand and the standard deviation for normal PDF, respectively. A 7-interval discrete normal PDF is used to generate demand states at each hour.

In order to combine different states of wind, solar and demand in each period, the scenario tree model is used in the proposed method [49,50]. Each scenario consists of three different states of wind and solar generation and demand values. Each scenario is assigned a weight, π_s, that reflects the possibility of its occurrence.

3.4. Demand Response Provider

Service Providers (SPs) are defined as the organizations providing services to electrical customers and to utilities. SP may be an electric utility, but that is not essentially the case. Customers can choose among competing SPs. Several third-party service providers offer demand response aggregation, energy management services, and other similar offers [51].

Demand Response Providers (DRPs) are also some types of SPs that provide demand response services to electrical customers and to utilities. DRPs aggregate small electricity customer's response: they register smaller customers, aggregate their offers, and submit the aggregated offers on behalf of them in the wholesale market DR program [52,53].

In this paper, DRPs are defined in order to aggregate offers for load reduction made by determined consumers. In particular, for each hour, a DRP submits its price-quantity offer as a package [52]. Each price-quantity package offered by a DRP consists of a minimum and maximum quantity for load reduction presented in several steps. Each step includes a load reduction quantity and an offer price for this reduction. The minimum quantity for load reduction refers to some customers that, in order to take part in a DR program, should turn off their appliances or a production line. So, the minimum amount for load reduction offer cannot be lower than the first appliance or production line rated power.

The equations for the ith DRP are the following ones from (11) to (14).

$$L_{Min}^i \le l_\xi^i \le L_\xi^i \quad \xi = 1. \tag{11}$$

$$0 \le l_\xi^i \le (L_{\xi+1}^i - L_\xi^i) \quad \forall \xi = 2, 3, \ldots, \Phi. \tag{12}$$

$$DR^E(i,t) = \sum_{\xi=1}^{\xi=\Phi} l_\xi^i \tag{13}$$

$$C^{DR}(i,t) = \sum_{\xi=1}^{\xi=\Phi} o_\xi^i \times l_\xi^i \tag{14}$$

where l_ξ^i is the accepted load reduction of DRP i at step ξ of the price-quantity offer package; Φ represents the number of steps of the price-quantity offer; o_ξ^i is the price offer of DRP i for load reduction at step ξ; L_{Min}^i is the minimum quantity of load reduction offered by DRP i; $DR^E(i,t)$ and $C^{DR}(i,t)$ are, respectively, the total accepted load reduction quantity and cost for the ith DRP at hour t.

At each hour, the sum of scheduled energy reduction and reserve provided by each DRP should not be greater than its maximum load reduction offer (L_{Max}^i). This means that the uncommitted load reduction capacity of each DRP's offer package during energy scheduling can be also scheduled for reserve requirement. The reserve prepared by DRPs is calculated as follows:

$$DR^E(i,t) + DR^R \le L^i_{Max} \tag{15}$$

$$RC^{DR}(i,t) = DR^R(i,t) \times q_{it} \tag{16}$$

where $DR^R(i,t)$ and $q_{i,t}$ are the scheduled reserve provided by DRP i and the reserve price for being in standby at hour t, respectively; L^i_{Max} represents the maximum quantity of load reduction offered by DRP i, and $RC^{DR}(i,t)$ is the reserve cost that is paid to DRP.

3.5. Objective functions and constraints

In this paper, two approaches have been integrated in the proposed DERs scheduling model: stochastic optimization method and augmented ε-constraint multi-objective method. Regarding augmented ε-constraint multi-objective method, operation cost and emission minimization were considered as objectives of the DERs scheduling model. Regarding stochastic optimization method, the cost function is modeled by a stochastic function that consists of two parts as described in the following.

The cost and emission objective functions as well as constraints are described as follows.

The proposed DERs scheduling method aims at minimizing two objective functions: cost (F_{cost}) and emissions ($F_{emission}$). The stochastic multi-objective optimization problem is formulated as follows:

$$Minimize\{F_{cost}, F_{emission}\} \tag{17}$$

In the stochastic cost objective F^{cost}, the involuntary load shedding is used in order to prevent committing more reserve in some scenarios with low probability. Involuntary load shedding refers to unplanned load shedding in which the operator should pay damage cost for power interruptions [54]. The Value of Lost Load (VOLL) is defined as the value that an average consumer loses from an unsupplied kWh of energy. The value of these reductions can be expressed as a customer damage function. While an involuntary load shedding for a consumer occurs, the damage cost is paid at VOLL to the consumer [55,56].

In day-ahead scheduling, the allocation of high reserve capacity leads to an increase of the operation costs as well as of air pollutant emissions. Thus, the proposed stochastic method determines the reserve requirements for each scenario based on a trade-off between the costs due to the reserve and to the expected energy not served. The load shedding option is considered only for some scenarios with very low probability of occurrence. In fact, in the operation of the real distribution system, it is expected that no involuntary load shedding occurs due to renewable generation variations. When a low probability renewable power scenario happens, if the scheduled reserve is not enough for compensating the power deviation, the DSO can purchase the required power from hour-ahead or real-time market [57,58]. As a result, it is not cost-effective to allocate the reserve for the worst case scenario in the day-ahead scheduling as this scenario has a very low probability of occurrence. Allocating the reserve for the worst case scenario leads, in fact, to an increase of the operation costs and air pollutant emissions due to the stand-by operation of some DGs required for providing spinning reserve. Moreover, some DERs lose the opportunity to participate in energy scheduling due to reserve commitment.

The total expected cost (F_{cost}) of the distribution network that should be minimized is modeled by a stochastic optimization function as follows [59]:

$$\begin{aligned} F_{cost} = \sum_{t=1}^{T}\left[P_g(t)\times\Omega_t + \sum_{j=1}^{J} fc(j,t) + SU(j,t) + RC_{DG}(j,t) + \sum_{i=1}^{I} RC^{DR}(i,t)\right] \\ + \sum_{t=1}^{T}\sum_{s=1}^{S}\pi_s \times \left[\sum_{j=1}^{J} C_{DG}(j,t,s) + \sum_{i=1}^{I} C^{DR}(i,t,s) + \sum_{n=1}^{N} ENS(n,t,s)\times V_t\right] \end{aligned} \tag{18}$$

where $P_g(t)$ represents the scheduled purchased power from the main grid at period t; Ω_t is the hourly electricity price of the open market; J and I represent, respectively, the number of DGs and DRPs; $fc(j,t)$ and $SU(j,t)$ represent, respectively, the fixed running and start-up costs of DGs; $RC_{DG}(j,t)$ and $RC^{DR}(j,t)$ are the reserve costs of DG j and DRP i in period t; π_s is the probability of scenario s. $C_{DG}(j,t,s)$ and $C^{DR}(j,t,s)$ represent, respectively, the hourly running cost of DG j and the cost due for load reduction provided by DRP i in period t and scenario s; ENS(n,t,s) and V_t are the Expected Energy Not Served (EENS) and the Value of Lost Load, respectively.

The stochastic expected cost objective function has two parts:

- The first-part components appear with probability one and are related to decision variables whose final values are determined during the day-ahead scheduling. These variables are not modified if some variations happen in renewable unit outputs or demand if compared with the predicted values. In other words, in each period, the variables of the first part get a same value whatever scenario happens. These variables are:
  - the cost of purchased power from the main grid;
  - the costs of reserve provided by DGs or DRPs;
  - the fixed running and start-up cost of DGs.
- The second-part components appear with a probability π_s during period t under realization of scenario s. Values of the second part variables are different in each scenario according to wind, solar and demand parameter in each scenario. So, the real amount of these variables will be determined in the real time. These variables are:
  - the generation running costs of DGs;
  - the load reduction costs of DRPs;
  - the cost of involuntary load shedding.

The output results of the stochastic programming are imported power from the main grid, DGs power output and committed reserve capacity and amount of load reduction and committed reserve provided by DRPs for each hour of day ahead scheduling horizon. Regarding DGs and DRPs, the values of the base case variable is considered as the output result for DG power and DRP load reduction. The base case refers to one of the scenarios in which generated wind and PV energy and demand values are equal to the predicted ones [59]. The changes of DGs output power and load reduction variables in each scenario, when compared with the base case determine the reserve that should be provided by DGs and DRPs in each scenario. In the proposed model, it is assumed that DGs should provide the spinning reserve in order to compensate the renewable and demand uncertainties. So, DG cannot be turned on in a scenario for providing reserve while it is turned off in the base case. As a result, the fixed and start-up costs of DGs are placed in the first part with probability one. In fact, whatever scenario happens in real time, DG on/off status is the same as the scheduled one, while only its output power may change according to each scenario. It means that if a DG is scheduled to be turned on in a scenario, it must be also turned on in the base case and vise versa. Moreover, the reserve capacity is determined the day-ahead and the reserve payment is carried out according with the day-ahead scheduled values. So, whatever scenario happens in real time, the reserve payment will not change. For this reason, the reserve cost is placed in the first part of the objective function with probability one.

In order to explain the reserve scheduling in the stochastic programming with an example, let's assume that the scheduled values for the base case in a period (output result) are: 4000 kW for the main grid, 700 kW for DG No. 1, 200 kW of load reduction for DRP No. 3. Also, let's consider a scenario in which 300 kW of renewable generation curtailment happens. This unbalanced condition between generation and consumption could be only compensated by DG or DRP. So, the main gird scheduled power still remains 4000 kW and the new values for the other variables are: 900 kW for DG No. 1 and 300 kW load reduction for DRP No. 3. As a result, the reserve capacity that is required for this scenario is 200 kW for DG No. 1 and 100 kW for DRP No. 3.

The cost function of a generator can be expressed mainly as a function of its real power output and can be modeled by a quadratic polynomial [60]. The total operational cost of a DG unit (like a diesel generator) with a quadratic cost function ($DGC(j, t, s)$) is given by:

$$DGC(j,t,s) = a_j \times u(j,t) + b_j \times P_{DG}(j,t,s) + c_j \times P_{DG}^2(j,t,s) + SU(j,t) \tag{19}$$

where a_j, b_j and c_j represent the cost coefficient of DG j; $P_{DG}(j, t, s)$ is the active output power of DG j in period t and scenario s; $u(j, t)$ represents the binary variable which shows the on or off state of DG j in period t; Sc_j is the start-up cost of DG j. In order to reduce the nonlinearity of the method, the non linear cost function of DG is approximated by a linear function that for practical purpose is indistinguishable from the nonlinear model [28].

The total DGs cost function consists of fixed, running and start-up costs given as follows:

$$fc(j,t) = a_j \times u(j,t) \tag{20}$$

$$C_{DG}(j,s,t) = b_j \times P_{DG}(j,t,s) + c_j \times P_{DG}^2(j,t,s) \tag{21}$$

$$SU(j,t) \geq Sc_j \times (u(j,t) - u(j,t-1)) \tag{22}$$

$$SU(j,t) \geq 0 \tag{23}$$

Accordingly, the reserve cost of DG ($RC_{DG}(j,t)$) is calculated as follows:

$$RC_{DG}(j,t) = R_{DG}(j,t) \times RP_{j,t} \tag{24}$$

where $RP_{j,t}$ and $R_{DG}(j,t)$ represent, respectively, the price offer for reserve and scheduled spinning reserve provided by DG j in period t.

Electrical loads are supplied by both DGs installed in the distribution network and conventional power plants of generation system in the main grid. The objective function related to the total emissions during the planning period is calculated as follows:

$$F_{emission} = \sum_{t=1}^{T} \left[(E_{CO_2}^{grid,t} \times P_g(t)) + \sum_{j=1}^{J} E_{CO_2}^{DG,j} \times P_{DG}(j,t) \right] \tag{25}$$

where $E_{CO_2}^{DG,j}$ is the CO_2 emission rate of DG j; $E_{CO_2}^{grid,t}$ is the average CO_2 emission rate of all committed power plants in the main grid at hour t. The output power of DGs in the base case ($P_{DG}(j,t)$), is considered in the emission objective function.

The following constraints are considered in the optimization problem:

(1) Power flow and load balance equation:

The power balance at node n in each period and scenario should be satisfied. In this paper the main focus is on active power scheduling of DGs and active load reduction of DRPs. Therefore, it is assumed that the reactive power output of DGs and the reactive load demand reduction of DRPs are considered based on the power factor of DGs and the same proportional of active power reduction of DRPs, respectively [46].

$$\begin{aligned} P_g(t) + \sum_{j\in n} P_{DG}(j,t,s) + \sum_{w\in n} P_{s,t}^{w} + \sum_{pv\in n} P_{s,t}^{pv} - D_{n,t,s} + \sum_{i\in n} DR^E(i,t,s) + ENS(n,t,s) \\ = \sum_{m=1}^{N} |V(n,t,s)||V(m,t,s)||Y_{n,m}| \cos(\delta(m,t,s) - \delta(n,t,s) + \theta_{n,m}) \quad \forall n,t,s \end{aligned} \tag{26}$$

$$\begin{aligned} Q_g(t) + \sum_{j\in n} Q_{DG}(j,t,s) + \sum_{w\in n} Q_{s,t}^{w} + \sum_{pv\in n} Q_{s,t}^{pv} - D_{n,s,t}^{Q} + \sum_{i\in n} QDR^E(i,t,s) + QENS(n,t,s) \\ = -\sum_{m=1}^{N} |V(n,t,s)||V(m,t,s)||Y_{n,m}| \sin(\delta(m,t,s) - \delta(n,t,s) + \theta_{n,m}) \quad \forall n,t,s \end{aligned} \tag{27}$$

where N is the total number of buses; n and m are index for buses; $P_{s,t}^{w}$, $P_{s,t}^{pv}$ and $D_{n,t,s}$ represent, respectively, the active power of wind turbine w, the active power of PV system pv and the active demand in period t and scenario s. The required load reduction from DRPs at each scenario are defined as $DR^E(i, t, s)$. $ENS(n, t, s)$ is the amount of involuntary load shedding at bus n in period t and scenario s. $Q_g(t)$, $Q_{DG}(i, t, s)$, $Q_{s,t}^{w}$, $Q_{s,t}^{pv}$, $QDR^E(i, t, s)$ and $QENS(n, t, s)$ represent, respectively, the reactive power related to the main grid, DG j, wind turbine w, PV system pv, DRP i and involuntary load shedding at bus n in period t and scenario s. $|V(n, t, s)|$ and $\delta(n, t, s)$ are, respectively, voltage amplitude and voltage angle at node n in period t and scenario s; $|Y_{n,m}|$ and $\theta_{n,m}$ represent amplitude and angle of element (n, m) of the admittance matrix, respectively;

(2) DRPs' constraints:

The scheduled reserves prepared by DRPs ($DR^R(i, t)$) in period t are defined as the additional load demand reduction of each DRP in each scenario, if compared to the base case. Choosing the maximum value guarantees that the scheduled load reserve can cover load reduction's requirement in all scenarios.

$$DR^R(i,t) \geq DR^E(i,t,s) - DR^E(i,t,0) \quad \forall s,i,t \tag{28}$$

where $s = 0$ refers to the base case and $DR^E(i, t, 0)$ represents the load reduction of DRP i in the base case and period t.

(3) DG power and reserve constraints:

The DG 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.

$$P_{DG}(j,t,s) \leq P_{DG,j}^{max} \cdot u(j,t) \quad \forall j,t,s \tag{29}$$

$$P_{DG}(j,t,s) \leq P_{DG,j}^{min} \cdot u(j,t) \quad \forall j,t,s \tag{30}$$

where $P_{DG,j}^{min}$ and $P_{DG,j}^{max}$ are the minimum and maximum limits of DG j output power, respectively.

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

$$R_{DG}(j,t) \geq P_{DG}(j,t,s) - P_{DG}(j,t,0) \quad \forall j,t,s \tag{31}$$

where $P_{DG}(j, t, 0)$ represents the scheduled output power of DG j in the base case and in period t.

(4) Network constraints:

The network operation constraints are as follows:

$$|S(n,m,t,s)| \leq S_{n,m}^{max} \quad \forall t \in \left\{1,\ldots T\right\}; \quad \forall n,m \in \left\{1,\ldots,N\right\} \tag{32}$$

$$V_n^{min} \leq V(n,t,s) \leq V_n^{max} \forall t \in \{1,\ldots T\}; \quad \forall n \in \{1,\ldots,N\} \tag{33}$$

$$P_g(t) \leq P_{sub}^{max} \quad \forall t \in \{1,\ldots T\} \tag{34}$$

where $|S(n, m, t, s)|$ is the apparent power flow from node n to m in period t and scenario s; $S_{n,m}^{max}$ is the capacity of the line/cable between node n and node m; V_n^{max} and V_n^{min} are the maximum and minimum voltage magnitude at node n, respectively; P_{sub}^{max} is the maximum power that can be drawn from the main substation.

3.6. Multi-objective augmented ε-constraint method

In order to deal with the trade-off between reducing the cost and the amount of air pollutants emission produced by conventional generators, the augmented ε-constraint method is used in the proposed method [61,62].

Generally, the augmented ε-constraint method is formulated as:

$$\begin{cases} Min\left(F_1(x) - \delta\displaystyle\sum_{k=2}^{K}\frac{s_k}{r_k}\right) \\ \text{subject to} \\ F_k(x) + s_k - e_k^z \quad k=2,\ldots,K;\ s_k \in R^+ \end{cases} \tag{35}$$

where

$$e_k^z = F_k^{max} - \left(\frac{F_k^{max} - F_k^{min}}{q_k - 1}\right) \times z, \quad z = 0,1,\ldots,q_k \tag{36}$$

where δ is a scaling factor; S_k is a slack variable; F_k^{max} and F_k^{min} represent the maximum and minimum values of the kth objective function, based on the payoff table, respectively; e_k^z is the zth range of kth objective function; r_k is the range of the kth objective function ($F_k^{max} - F_k^{min}$), and q_k is the number of equal part.

In the augmented ε-constraint method, firstly the payoff table should be set up. The payoff table refers to the table with the results from the individual optimization of the each objective function. After the calculation of the payoff table, one of objective function is considered as the main objective function (F_1) where the range of each one of the $K-1$ objective functions are going to be used as constraints. Then, the range of the kth objective function is divided to $q_k - 1$ equal intervals. Thus, in total (q_k) grid points are obtained that are used to vary parametrically the right-hand side (e_k^z) of the kth objective function. A desirable characteristic of the ε-constraint method is that the density of the efficient set representation can be controlled by properly assigning the values to the q_k. With a higher number of grid points, a denser efficient set is obtained but with a higher computational time. A trade-off between the density of the efficient set and time consuming is always necessary.

Comparing to the ordinary ε-constraint method, the main objective function is augmented by the sum of the slack variables s_k. In order to avoid any scaling problems the s_k in the second term of the objective function is replaced by $\delta \times (s_k/r_k)$. This mechanism prevents generating the inefficient solutions. It can mathematically be proven that the augmented ε-constraint method only generates efficient solutions. Its proof can be found in [62].

Table 1
Payoff table.

	F^{cost}	$F^{emission}$
Min F^{cost}	F_{Min}^{cost}	$F_{Max}^{emission}$
Min $F^{emission}$	F_{Max}^{cost}	$F_{Min}^{emission}$

In solving each of the sub problems all the constraints of the model should be also considered. By solving each optimization subproblem, one Pareto-optimal solution is obtained.

In the proposed method, there are two objective functions ($F_2 = F_{cost}$ and $F_2 = F_{emission}$). The number of intervals for the objective function $F_{emission}$ is considered to be equal to 19 ($q_2 = 20$). The payoff table for two objective functions is calculated as shown in Table 1:

3.7. Best compromise solution

Decision making is an important part of the human life. Everybody in every situation faces different options that should choose the best one among them. In general, there are many different methods such as Analytical hierarchy process (AHP) [63], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [53], fuzzy set [64], Knee set [65], max–min [66] and so on (they are called Multi Attribute Decision Making (MADM)) that facilitate selection of the best option. Each of the mentioned methods can be applied by system operator. When the Pareto-optimal solutions are obtained, one of the solutions can be chosen as the best compromise solution by using one of the above methods. However, the decision maker's attitude and preference should determine the best compromise solution. It should be noted that the decision maker can have the measures of the consequences [67] of its choices in terms of both costs and emissions and consequently select the best compromise solution also considering regulatory limits related to emissions or economic constrains related to distribution systems operation.

In this paper, generating the Pareto front is the main goal of the proposed method and the selection of one of the Pareto solutions is carried out only for analyzing the results. In order to select the best compromise solution, it is assumed that the DSO, as the decision maker, determines maximum allowed values for both total operation cost and emissions. So, the proposed decision-aid approach is used to analyze some non-dominated solutions while the final decision is made by the decision maker, not by the analyst. The approach suggested by the authors is one of the possible ways, but using a reference trade-off (k$/ton) set by the decision maker is another possibility.

4. Case study

The proposed DERs scheduling method was applied to a modified 69-bus 11-kV radial distribution system having two substations [68] as shown in Fig. 3. The voltage limits are taken to be ±6% of nominal and the thermal limits for lines are 1.5 MVA. The hourly electricity demand of the test system is illustrated in Fig. 4 and the share of each bus of hourly demand is given in Table 2. Also, Table 3 provides the hourly electricity price of open market according to [69].

The real hourly wind speeds information has been taken from Willy Online Pty Ltd whether forecast website and shown in Fig. 5 [70]. All wind turbines installed in the test system are of the same type with specifications power rated of 800 kW, cut-in speed of 4 m/s, nominal speed of 14 m/s, and cut-out speed of 25 m/s. Five 100 kW PV systems are installed in the test system: each of them is

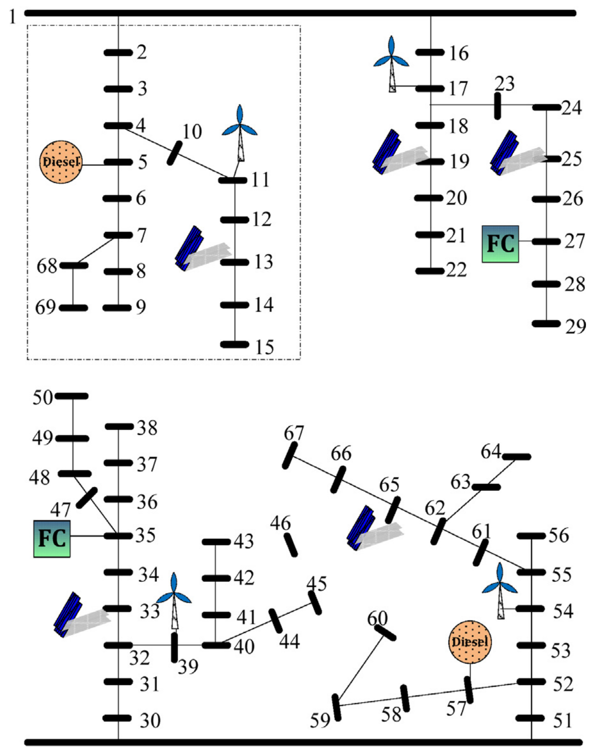

Fig. 3. 69 Bus distribution test system.

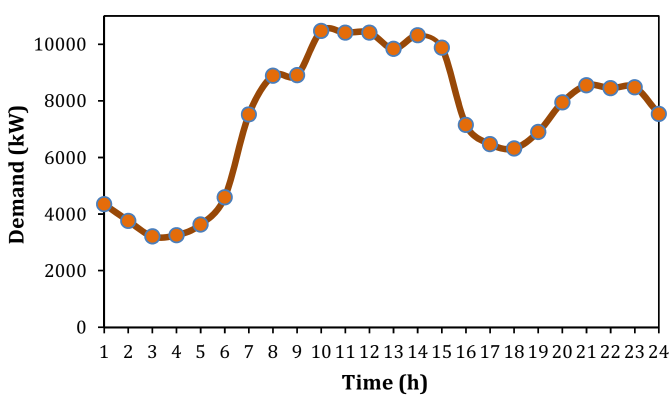

Fig. 4. The hourly electricity demand of the test system.

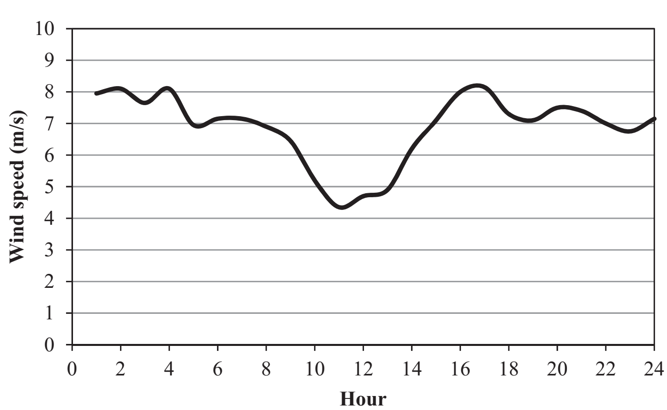

Fig. 5. Hourly wind speed forecast.

Table 2
The share of each bus from hourly demand.

Bus	%	Bus	%	Bus	%
1	0	24	1.4	47	1.2
2	1.5	25	1.2	48	1.3
3	1.4	26	1.5	49	0.5
4	3.85	27	1.1	50	1.6
5	0.9	28	0.9	51	1.4
6	1.5	29	1.4	52	1.2
7	1.2	30	1.2	53	1.4
8	0.8	31	0.9	54	1.6
9	0.6	32	0.7	55	1.8
10	1.7	33	0.05	56	0.8
11	1.3	34	1.5	57	3.4
12	2.9	35	1.6	58	1.3
13	1.4	36	2.2	59	1.1
14	1.7	37	0.9	60	0.8
15	1.6	38	1.8	61	2.4
16	1.8	39	1.1	62	3.7
17	1.3	40	1.4	63	1.3
18	1	41	2.1	64	1.2
19	2.5	42	1.3	65	1.5
20	0.9	43	1.5	66	2.1
21	0.4	44	1.3	67	1.4
22	2.1	45	1.6	68	1.3
23	1.7	46	1.7	69	1.3

Table 3
Hourly electricity price of the open market.

t	1	2	3	4	5	6
$/kWh	0.033	0.027	0.020	0.017	0.017	0.029
t	7	8	9	10	11	12
$/kWh	0.033	0.054	0.215	0.572	0.572	0.572
t	13	14	15	16	17	18
$/kWh	0.215	0.572	0.286	0.279	0.086	0.059
t	19	20	21	22	23	24
$/kWh	0.050	0.061	0.181	0.077	0.043	0.037

composed of 10×10 kW solar panels with $\eta = 18.6\%$ and $S^{PV} = 10\ \mathrm{m}^2$ [71]. The average hourly solar irradiance is shown in Fig. 6 [72]. Also, two diesel generator and two Fuel Cell (FC) sets are installed in the test system. The wind turbines and PV systems are assumed to have fixed power factors equal to 1 while fuel cells and diesel generators are assumed to have fixed power factors of 0.9 lagging. The VOLL, required to estimate the social cost of interruptions, is assumed to be 1000$/MWh [55,56].

The fuel cost and emission rate of the diesel generator and FC units are given in Table 4 [22,73,74]. The spinning reserves of DGs are priced at a rate equal to the 25% of their highest marginal cost of the energy production [75]. In this study, it is assumed that the main grid generation system is typically composed of nuclear, hydro, gas steam, coal and gas combined cycle power plants. It is also

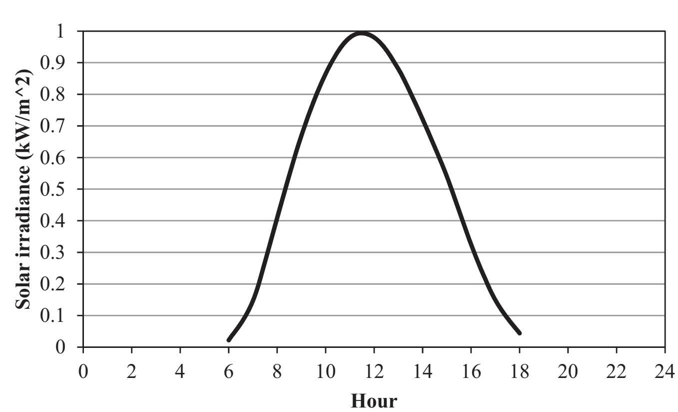

Fig. 6. Hourly solar irradiance forecast.

Table 4
Cost coefficients and emission rate of DGs.

Unit	Cost coefficient				Technical constraints		Emission
	a_j ($)	b_j($/kWh)	c_j(S/kWh^2)	Start-up ($)	P_{min} (kW)	P_{max} (kW)	CO_2 (kg/MWh)
Diesel	38	0.058	0.00025	2	50	1000	890
FC	25	0.468	–	3	100	1000	410

Table 5
Price-quantity offer packages of DRPs.

	Quantity (kW) / Price ($/kWh)			
DRP1	0–100	100–170	170–220	220–320
	0.45	0.48	0.51	0.53
DRP2	0–75	75–125	125–275	275–375
	0.40	0.45	0.53	0.61
DRP3	0–50	50–100	100–180	180–280
	0.22	0.41	0.53	0.56
DRP4	0–60	60–160	160–210	210–285
	0.26	0.47	0.51	0.55

supposed that, according to a unit commitment program at each hour, the average CO_2 emission rates of conventional power plants in the main grid for low (hours 23–24 & 1–6), medium (hours 6–20) and high (hours 20–23) load hours are of 80, 462, 985 kg/MWh, respectively [74]. The Load buses areas of each DRP are shown in Fig. 3 and DRPs' price–quantity offer packages are presented in Table 5.

The above formulation has been implemented in GAMS [76] using Mixed-Integer Non-Linear Programming (MINLP) solver DICOPT [77] on a PC with Quad-Core 3.2 GHz CPU and 48 GB of RAM. The simulation code considering 175 scenarios consists of 74,400 constraints, 105,218 decision variables among which 105,122 are continuous variables and 96 are binary variables. The computation time for the proposed multi-objective method is 413 s.

In order to evaluate the effects of cost and emission objectives in energy and reserve scheduling the proposed method is tested in 3 different cases:

- Case 1: only the cost objective function minimization is considered;
- Case 2: only the emission objective function is considered;

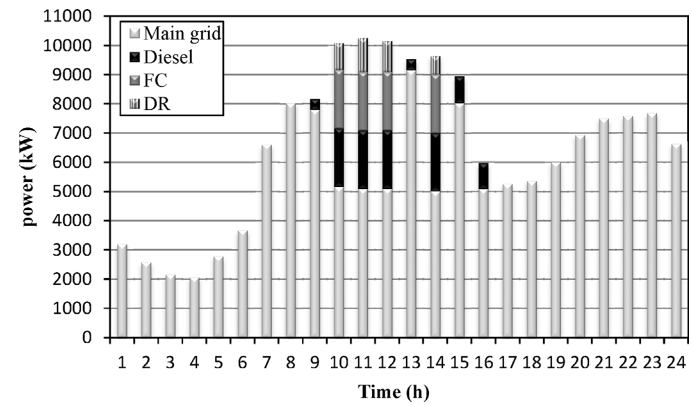

Fig. 7. Energy resources scheduling in case 1.

- Case 3: the two objective functions are considered in a multi-objective optimization using augmented ε-constraint multi-objective optimization.

4.1. Cost vs. emission objectives

The DERs scheduling in cases 1 and 2 in which the cost and emission objective functions are only considered separately are shown in Figs. 7 and 8.

As shown in Fig. 7, the DGs and DRPs participate during hours 10–15 when the electricity prices are high as these resources can supply energy requirements at a lower price. So, the total operation costs are reduced. However, in case 2 where the emission reduction is the objective of DERs scheduling, the results are different. As shown in Fig. 8, the FC units are forced to be turned on in most of the periods due to their low emission rate. Also, as the load demand reduction reduces the emissions, the maximum load demand reductions are scheduled during all hours. The diesel

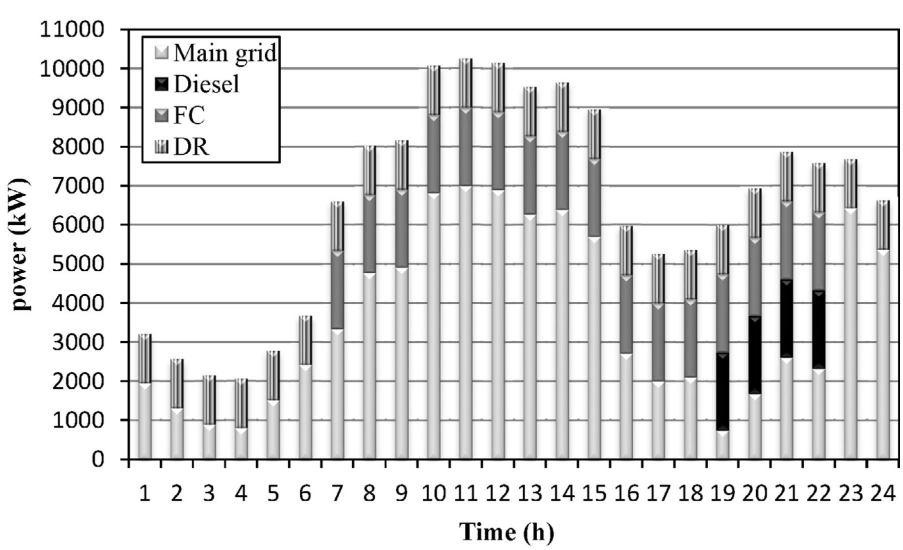

Fig. 8. Energy resource scheduling in case 2.

Table 6
Payoff table of the ε-constraint multi-objective method.

	Cost (k$)	Emission (Ton)
Min F^{cost}	34.61	77.43
Min $F^{emission}$	67.50	56.27

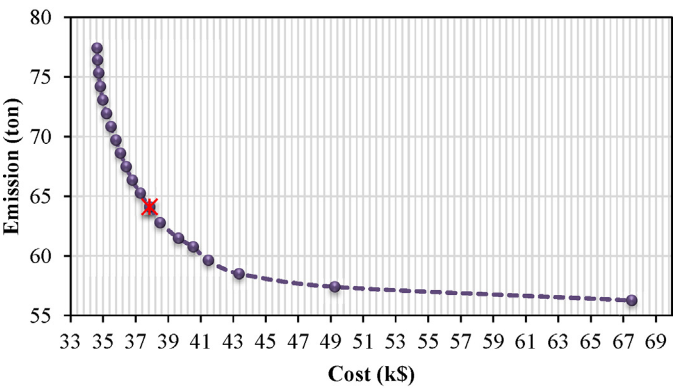

Fig. 9. Pareto-optimal solution.

generators are only turned on during hours 19–22, when the average emission rate of the main grid generation system is very high.

4.2. Multi-objective optimization

In case 3, the DERs scheduling is carried out considering both cost and emission objective functions. The augmented ε-constraint multi-objective method is implemented in order to carry out the multi-objective optimization. The maximum and minimum values of the cost and emission functions are shown in Table 6 (payoff table). Each set of these values has been obtained by individual minimization of cost and emissions objective functions. The Pareto-optimal solution obtained from the augmented ε-constraint multi-objective method, is shown in Fig. 9. In order to select one of Pareto optimal solutions for analyzing the results, it is assumed that the costs and emissions should be lower than 38 k$ and 65 ton, respectively. So, the Pareto-optimal solution No. 13 has been selected as the best compromise solution (shown by star in Fig. 9).

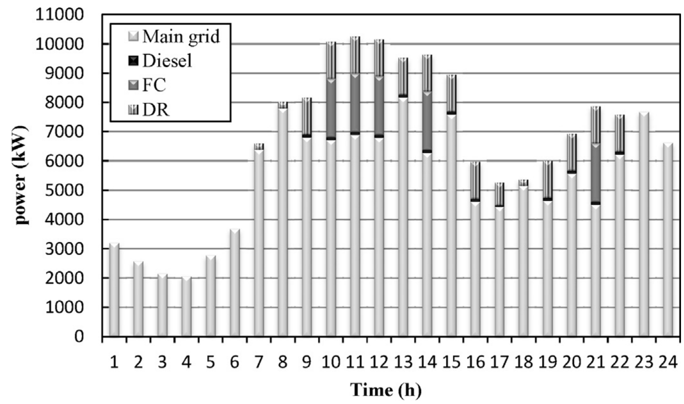

Fig. 10. Energy resources scheduling results of the best compromise solution in case 3.

This method allows the decision maker having the measures of the consequences in terms of both costs and emissions and chooses the best compromise solution considering the sensitivity of the two objective functions also with regards to the single objective optimization problems. More in details, the best compromise solution, if compared to the solution that only minimizes the operation costs, allows reducing the emissions by about 13 ton with an increase of about 3.2 k$.

The energy and reserve scheduling result for the best compromise solution derived from the multi-objective method are shown in Figs. 10 and 11, respectively.

As shown in Fig. 10, the FC units and load demand reduction have been utilized during high price hours as well as during high emission rate hours in order to reduce both cost and emission objectives. As shown in Fig. 11, during hours 1–8 and 23–24, DRPs are the only providers of reserves. So, it is not necessary to turn on the diesel generators in order to be in standby mode only for providing spinning reserve. During these periods, the unpredicted renewable generation curtailments and demand fluctuation are compensated by DR programs. However, during hours 9–22 when the electricity price and average emissions rate of the main grid generation system are high, it was preferred using the DR program in order to provide load demand reduction in energy scheduling instead of providing reserve capacity. During these periods, in fact, the load reductions

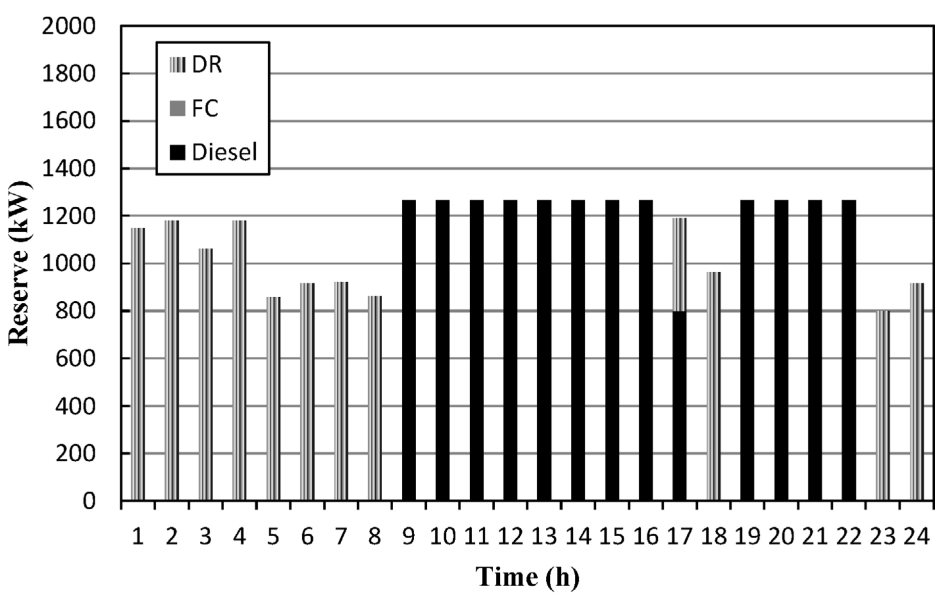

Fig. 11. Scheduled reserve results of the best compromise solution in case 3.

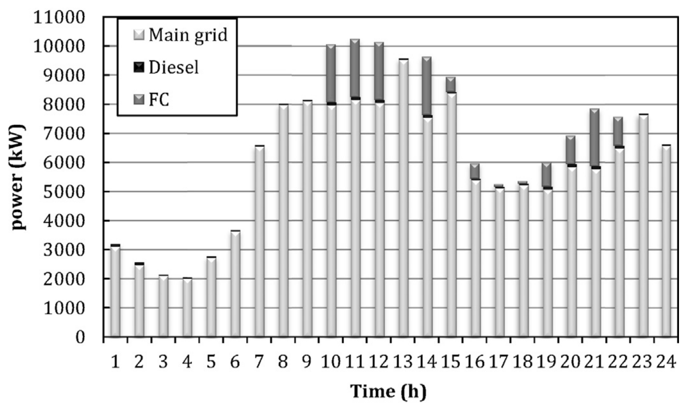

Fig. 12. Energy resources scheduling results of the best compromise solution without considering DR.

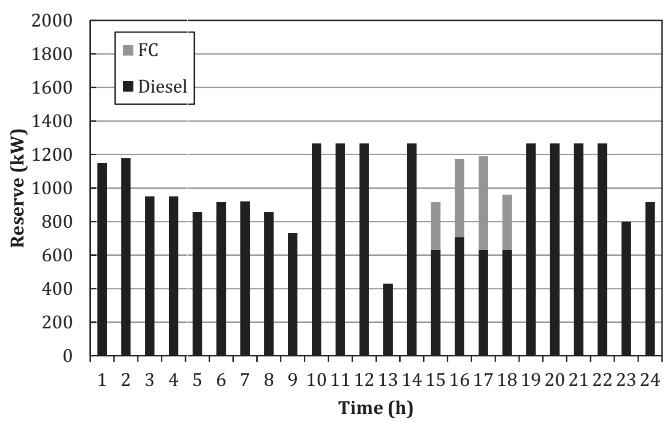

Fig. 13. Scheduled reserve results of the best compromise solution without considering DR.

Table 7
Case 3 with and without considering DR program.

	Operation cost ($)	Emission (Ton)
Without DR	39,822	70.763
With DR	37,848	64.120

significantly reduce both the cost and emissions. Moreover, the DGs scheduled power has been reduced in order to provide the reserve capacity that also helps to further reduce emissions.

In order to evaluate the role of DRPs in the proposed DERs scheduling method, the augmented ε-constraint multi-objective method has been also carried out without considering DR programs. The energy and reserve scheduling results for the best compromise solution without considering DR programs have been illustrated in Figs. 12 and 13, respectively.

As shown in Figs. 12 and 13, the diesel generators have been forced to be turned on in all hours in order to provide all reserve capacity. So, the emissions and operation cost of the system in the scheduling horizon are higher. Table 7 shows a comparison between cost and emission for the best compromise solutions in case 3 with and without considering DR program. As shown, demand side participation in energy and reserve scheduling allows reducing the operation cost and air pollutant emissions.

5. Conclusion

A DERs scheduling method for smart distribution systems considering demand side participation has been proposed in this paper. The intermittent natures of wind and solar generation as well as demand forecast error have been modeled by a stochastic programming method. Moreover, augmented ε-constraint multi-objective method was used in order to consider both of operation cost and emission objectives. Simulation results demonstrated that the demand side participation in energy and reserve scheduling allows reducing the total operation costs and emission. In order to show the capability of the multi-objective optimization, the scheduling has been compared for the single objective and the multi-objective problems. Simulation results evidenced that the inclusion of the emission target increased the operation cost. In addition, DR usage is higher when the emission objective is taken into account. The results showed that DR participation in reserve scheduling changes DGs scheduling and prevent DGs to be stand-by only for providing reserve.

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