Electrical Power and Energy Systems 63 (2014) 218–225

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Stochastic operational scheduling of smart distribution system considering wind generation and demand response programs

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A R T I C L E I N F O

Article history:
Received 15 May 2013
Received in revised form 13 May 2014
Accepted 19 May 2014

Keywords:
Distribution system
Reserve
Stochastic programming
Demand response
Wind power

A B S T R A C T

In this paper a stochastic operational scheduling method is proposed to schedule energy and reserve in a smart distribution system with high penetration of wind generation. The wind power and demand forecast errors are considered in this approach and the reserve is furnished by both main grid generators and responsive loads. The consumers participate in both energy and reserve scheduling. A Demand Response Provider (DRP) aggregates loads reduction offers in order to facilitate small and medium loads participation in demand response program. The scheduling approach is tested on an 83-bus distribution test system over a 24-h period. Simulation results show that the proposed stochastic energy and reserve scheduling with demand response exhibits a lower operation cost if compared to the deterministic scheduling.

Introduction

The upgrading of power system toward a smart grid is being developed to improve reliability, facilitate the integration of different types of renewable energies, and improve load management. With the development of the smart grid, more Distributed Energy Resources (DER) are deployed such as distributed wind and solar units, as well as technologies for expanded demand side management programs.

Demand response (DR) is one of the key approaches that can fully be enabled by smart grids. DR is a set of actions taken to reduce consumer electricity consumption when contingencies, such as unit outage or unpredictable change in demand or renewable generation, occur that threaten supply demand balance. Moreover, if market conditions that raise electric supply costs occur, DR is one of the best solutions. In other words, DR programs and tariffs maybe designed to improve the reliability of the electric grid or to lower the use of electricity during peak hours, thus reducing the total system operation costs.

Wind power generation is one of the most important renewable resources used in many countries to replace conventional power plants and reduce greenhouse gas emissions [1]. However, since wind generation can only be controlled by ‘‘spilling wind’’ and its power output cannot be forecasted with great accuracy, a significant increase in the prediction of the power produced from wind energy has a considerable impact on the way in which scheduling and dispatch are carried out. 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 wind generation changes or a combination of both [2].

Determining the optimal amount of reserve that must be provided as a function of the system conditions is thus an important and timely issue. Moreover, the reserve scheduling is simultaneously carried out with energy scheduling [3]. There are two types of methods used for reserve scheduling in the literature: specifically deterministic and stochastic methods. In the deterministic approach, the amount of reserve requirement in each period is determined before the energy and reserve scheduling [4,5]. Generally, the amount of reserve is determined considering the capacity of the largest online generators, load demand and the percentage of renewable generation. Some previous researches evidence that the probabilistic nature of renewable generation and load demand can be considered for scheduling reserve [1]. In the stochastic approach, the amount of reserve requirement is settled during the energy and reserve scheduling procedure [6–8]. The situation (e.g. unpredicted generators outage and wind power and load demand fluctuations) in which the reserve is needed in order to compensate the power generation shortage is generally modeled by scenarios and the amount of reserve is determined according to the probability of each scenario.

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http://dx.doi.org/10.1016/j.ijepes.2014.05.062
0142-0615/

A stochastic model of wind power generation based on an optimal power flow scheduling/dispatching program has been presented in [9]. This model incorporates the error in wind power forecasts by using a relative frequency histogram or probability. In [10], a differential evolution algorithm for integrated energy and spinning reserve dispatch with uniform prices has been proposed. In [11], covariant matrix adaptation with evolution strategy using mean learning technique has been proposed to solve an economic dispatch problem and to find the optimal scheduling/allocation of energy and spinning reserves among thermal and wind generators. The uncertainty of wind power generation has been modeled by Weibull probability density function. However, the objective function has been considered such as in a deterministic method. A probabilistic approach to investigate the multi-objective distribution feeder reconfiguration considering wind turbines has been presented in [12]. This probabilistic method considered the uncertainty regarding the load demand forecast errors as well as the wind turbines output power variations. In [13], a stochastic joint energy and spinning reserve market clearing model has been proposed based on a multi-objective mixed integer nonlinear programming with three objective functions. Wind power generation uncertainty and demand response programs are not considered in this work. A stochastic bidding strategy of a microgrid in a joint day-ahead market of energy and spinning reserve service has been proposed in [14] in which uncertainty of renewable DG units' output power and load demand has been taken into account.

Today, ancillary services (such as voltage control, reactive power contribution and reserve capacity) are procured by the Transmission System Operator (TSO), largely from large power producers, to manage the system as whole. With the introduction of distributed generation and information and communication technologies, in future, it will be essential that also DSO will leave the actual passive management philosophy and become active in the management of the distribution system, thus also participating in procurements of ancillary services [15]. Moreover, DSOs are also responsible for ensuring that the dispatch of generation and allocation of reserves is correctly managed in order to maintain the power flows on distribution network within security and operational limits. Thus, active DSOs should be allowed to coordinate new system services such as ancillary services from Distributed Energy Resources (DER) [15].

Eventually, in order to achieve an efficient use of DER, DSOs will have to contract energy- and capacity-related products, and it is therefore expected that they will employ market-based mechanisms such as procurement auctions, similar to the ones TSOs are currently using to procure reserves [16].

Making demand side involved in the energy and reserve operational planning has opened a wide range of new possibilities for which demand elasticity has increased [17–19]. In [20], a model to support virtual power plants in DR programs' management has been presented in which all the existing energy resources (generation and storage units) and the distribution network are considered. The result showed that for higher values of network total load demand the use of DR can have a great impact in reducing both electricity prices and operation costs, namely in situations of absence of wind and solar power generation.

To the best of our knowledge, no stochastic energy and reserve scheduling method in distribution system considering uncertainties related to electricity price, wind power and load demand and in which the consumers can provide both energy and reserve services has been reported in the literature. Accordingly, in this paper a stochastic approach for energy and reserve scheduling of distribution systems is presented in which various types of demand response programs are taken into account. The contributions of this paper are highlighted as follows:

- Aggregate real-time price, wind power and load demand uncertainties.
- Consider load demand participation in both energy and reserve scheduling.
- Evaluate stochastic scheduling of energy and reserve in a distribution system.

The rest of the paper is organized as follows: Section 'Demand response programs' describes different types of demand response programs. The uncertainty modeling of electricity prices, wind power and load demand is explained in Section 'Uncertainty modeling'. In Section 'Energy and reserve scheduling', the stochastic scheduling of energy and reserve is formulated. Some simulation results are described in Section 'Case study' and finally the concluding remarks are presented in Section 'Conclusion'.

Demand response programs

In the proposed method, a DR program is provided by Demand Response Providers (DRP) and large individual consumers (e.g. industrial loads) [21,22]. The DRP acts as a medium between Distribution System Operator (DSO) [23] and small customers and enable the participation of small customers in DR programs. DR programs are characterized as load reduction in energy scheduling and reserve capacity in reserve scheduling carried out by DSO [24,25].

Each DRP submits load reduction offers as different price-quantity offer packages. In the price-quantity offer package, the minimum (L^i_{Min}) and maximum (L^i_{Max}) load reduction is determined. Also, the load reduction is divided into several steps each having a specific price. The equations for the ith DRP are the following ones from Eqs. (1)–(4).

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

$$0 \leqslant l^i_j \leqslant \left(L^i_{j+1} - L^i_j\right) \quad \forall j = 1, 2, \ldots, Max. \tag{2}$$

$$DP^E(i,t) = \sum_{j=1} l^i_j \tag{3}$$

$$DC^E(i,t) = \sum_{j=1} o^i_j \cdot l^i_j \tag{4}$$

where l^i_j is the accepted load reduction of DRP i in step j of price-quantity offer package; L^i_j and L^i_{j+1} represent, respectively, the start and end points of step j; $DP^E(i, t)$ and $DC^E(i, t)$ are, the total accepted load reduction quantity and payment for the ith DRP in period t, respectively.

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^i_{Max}). The reserve prepared by DRPs is calculated as follows:

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

$$DC^R(i,t) = DP^R(i,t) \times q^{R,p}(i,t) \tag{6}$$

where $DP^R(i, t)$ and $q^{R,p}(i, t)$ are the scheduled reserved provided by DRP i and the reserve price for being in standby in period t, respectively; $DC^R(i, t)$ is the reserve cost that is paid to DRP.

The equations of individual loads (ILs) participating in both energy reduction and for reserve supply are given as follows:

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

$$IC^E(b,t) = IL^E(b,t) \times q^{E,I}(b,t) \tag{8}$$

$$IC^R(b,t) = IL^R(b,t) \times q^{R,I}(b,t) \tag{9}$$

where $IL^E(b, t)$ and $IL^R(b, t)$ are, the scheduled load reduction and reserve prepared by individual consumer b in period t, respectively;

$IL_b^{max}(b,t)$ is the maximum load reduction offered by consumer b in period t; $q^{E,I}(b,t)$ and $q^{R,I}(b,t)$ are the price offer of individual load b for energy reduction and being in standby for reserve in period t, respectively. The cost of load reduction and committing reserve that are paid to individual loads participating in DR programs are $IC^E(b,t)$ and $IC^R(b,t)$, respectively.

Uncertainty modeling

A distribution system operator encounters three major sources of uncertainty, namely future real-time prices, future loads and intermittent renewable generation [26,27]. In this section, the uncertainty of future wind power, electricity price and load demand is modeled as multiple different scenarios. Then, the scenario-based stochastic programming method is employed here to handle the uncertainties [28].

Wind generation

The model used to simulate possible scenarios of the wind speed forecast errors is based on autoregressive moving average series (ARMA). It can be defined as [29]:

$$\Delta V(0) = 0, \quad Z(0) = 0 \tag{10}$$

$$\Delta V(t) = \alpha \Delta V(t-1) + Z(t) + \beta Z(t-1)$$

where $\Delta V(t)$ is the wind speed forecast error in period t; $Z(t)$ is a random Gaussian variable with standard deviation δ_z; α and β are parameters.

The wind speed scenario v_k^t in period t can be calculated as the sum of the wind speed forecast v_f^t and the wind speed forecast error scenario Δv_k^t, i.e. $\Delta V(t)$:

$$v_k^t = v_f^t + \Delta v_k^t \quad \forall k \in N_k \tag{11}$$

where N_k is number of wind speed forecast error scenarios.

The parameters δ_z, α and β can be identified by using the least-square fitting, minimizing the difference between sample forecast error variance based on data from the studied area, and modeled forecast error variance.

The output power of the wind turbine corresponding to each wind speed is calculated using the wind turbine power curve parameters as described by Eq. (12).

$$P_{w,k}^t = \begin{cases} 0, & 0 \leqslant v_k^t \leqslant v_{ci} \\ P_{rated} \times \frac{(v_k^t - v_{ci})}{(v_r - v_{ci})}, & v_{ci} \leqslant v_k^t \leqslant v_r \\ P_{rated} & v_r \leqslant v_k^t \leqslant v_{co} \\ 0, & v_{co} \leqslant v_k^t \end{cases} \tag{12}$$

where $P_{w,k}^t$ is the output power of wind turbine w according to wind speed scenario v_k^t; v_{ci}, v_r and v_{co} are the cut-in speed, rated speed and cut-off speed of the wind turbine, respectively; P_{rated} represents the total rated power of wind turbines.

Price uncertainty

The uncertainties on real-time prices is taken into account using time-series approaches [30] which enable constructing a set of scenarios. The time series ARMA model is used to predict hourly prices in the electricity markets by generating likely scenarios. More details on this method are given in [30].

Load demand uncertainty

Load uncertainty is modeled based on the load forecast errors. Here, a Gaussian distribution with specific lower and upper limits is used to model the probability density function (PDF) of the hourly load forecast errors. The parameters of PDF can be estimated from historical hourly load data by using curve fitting. The load scenario $P_{load,k}^t$ in period t can be calculated as the sum of the load forecast $P_{load,f}^t$ and the load forecast error scenario $\Delta P_{load,k}^t$:

$$P_{load,k}^t = P_{load,f}^t + P_{load,k}^t \quad \forall k \in N_k \tag{13}$$

where N_k represents number of load demand forecast error scenarios.

Scenario generation and reduction

Latin Hypercube Sampling (LHS) is a sampling method that ensures a full coverage of the range of variables by maximally stratifying marginal distribution [31]. In LHS, the distribution of a random variable is divided into intervals with equal probability, and a state is randomly selected within each interval. Therefore, LHS is used to sample day-ahead wind speed, market price and load forecast error. According to aforementioned day-ahead electricity price, wind speed, and load forecast error distributions, the cumulative distributions of each error variable is divided into several equiprobable intervals. A forecast error value is selected randomly from each interval. Then electricity price, wind speed, and load scenario can be generated considering the forecast and error values. Details of LHS can be found in [32,33].

The number of scenarios generated by LHS is huge, and the computational effort would be really expensive to solve scenario-based stochastic energy and reserve scheduling with all of these scenarios. Therefore, it is necessary to consider a limited subset of scenarios without losing the generality of the original set. The scenario reduction technique can reduce the number of scenarios effectively and maximally retain the fitting accuracy of samples. The backward scenario reduction technique is used here as described in [34].

Energy and reserve scheduling

In this model, DSO is responsible for energy and reserve scheduling in distribution networks [35–37]. In order to show the advantages of the energy and reserve scheduling using the proposed stochastic method, it is compared with a deterministic method. Accordingly, in this section, the formulations of the energy and reserve scheduling using deterministic and stochastic methods are explained.

Deterministic method

The objective function of the deterministic method (OF^{Det}) is the total operation cost of the distribution system that should be minimized:

$$OF^{Det} = \sum_{t=1}^{T} \left[P_{grid}(t) \times T_E^t + R_{grid}(t) \times T_R^t + \sum_{b \in B} IC^E(b,t) + IC^R(b,t) + \sum_{i \in I} DC^E(i,t) + DC^R(i,t) \right] \tag{14}$$

where $P_{grid}(t)$ and $R_{grid}(t)$ are the scheduled purchased energy and reserve from the main grid in period t, respectively. T_E^t and T_R^t are the hourly forecasted electricity and reserve price of electricity, respectively.

The constraints of the deterministic method are given as follows:

- Load balance

$$P_{grid}(t) + \sum_{w=1}^{W} P_{w,f}^{t} = P_{load,f}^{t} - \sum_{i} DP^{E}(i,t) - \sum_{b} IL^{E}(b,t) \tag{15}$$

where $P_{w,f}^{t}$ and $P_{load,f}^{t}$ are the forecasted wind power of turbine w and load demand in period t, respectively.

- Reserve constraint

The required reserve for each period in the deterministic method (R_t) is determined based on a percentage of forecasted load demand and wind power [1,5].

$$R_t = \sigma_w^t \cdot \sum_{w=1}^{W} P_{w,f}^{t} + \sigma_{load}^{t} \cdot P_{load,f}^{t} \tag{16}$$

$$DP^{R}(t) + IL^{R}(t) + R_{grid}(t) \geqslant R_t \tag{17}$$

where σ_w^t and σ_{load}^t represent forecast error values for wind power and load demand in period t, respectively.

Stochastic method

In order to consider the uncertain natures of wind power, load demand and electricity price within the energy and reserve scheduling, a two-stage stochastic programming framework is presented [28]. Variables pertaining to the energy and reserve costs and payments that are made before the realization of any one of the scenarios should be considered in the first stage of this model. In the second stage of the model, variables pertaining to each particular scenario at each time period should be considered.

The involuntarily load shedding is used in this model to prevent committing more reserve in some scenarios with low probability and refers to unplanned load shedding in which the operator should pay damage costs for power interruptions [6]. The Value of Lost Load (VOLL) is defined as the value that an average consumer losses from an unsupplied kW h of energy. The value of these losses can be expressed as a customer damage function. While an involuntarily load shedding for a consumer occurs, the damage cost is paid at VOLL to this consumer.

The total expected cost of the distribution network represents the objective function of the stochastic model that should be minimized [8]. The objective function has two parts: the first one is the sum of contracting energy and reserve costs which should be paid to the market operator and to loads participating in DR programs, while the second part is the operational cost associated to each scenario.

The first part of objective function takes into account the total contracting energy and reserve costs (CC) and is given as follows:

$$CC = \sum_{t=1}^{T} \left[P_{grid}(t) \times T_E^t + R_{grid}(t) \times T_R^t + \sum_{b \in B} IC^{E}(b,t) + IC^{R}(b,t) + \sum_{i \in I} DC^{E}(i,t) + DC^{R}(i,t) \right] \tag{18}$$

The second part of objective function takes into account the operational cost associated to each scenario ($SC(s)$) and is given as follows:

$$SC(s) = \sum_{t=1}^{T} \left[Ps_g(s,t) \times T_E^{t,s} + \sum_{b \in B} IC^{s}(b,t,s) + \sum_{i \in I} DC^{s}(i,t,s) + ENS(s,t) \times voll(t) \right] \tag{19}$$

where $Ps_g(s,\ t)$ and $T_E^{t,s}$ are, respectively, the required purchased power from the main grid and the real-time electricity price in scenario s at period t; $DC^s(i,\ t,\ s)$ and $IC^s(b,\ t,\ s)$ are the costs associated to both groups of load reductions in scenario s at period t, respectively; $ENS(s,\ t)$ and $voll(t)$ are the Expected Energy Not Served (EENS) and Value of Lost Load, respectively. So, $SC(s)$ represents the cost associated to the actual deployment of reserve in each scenario.

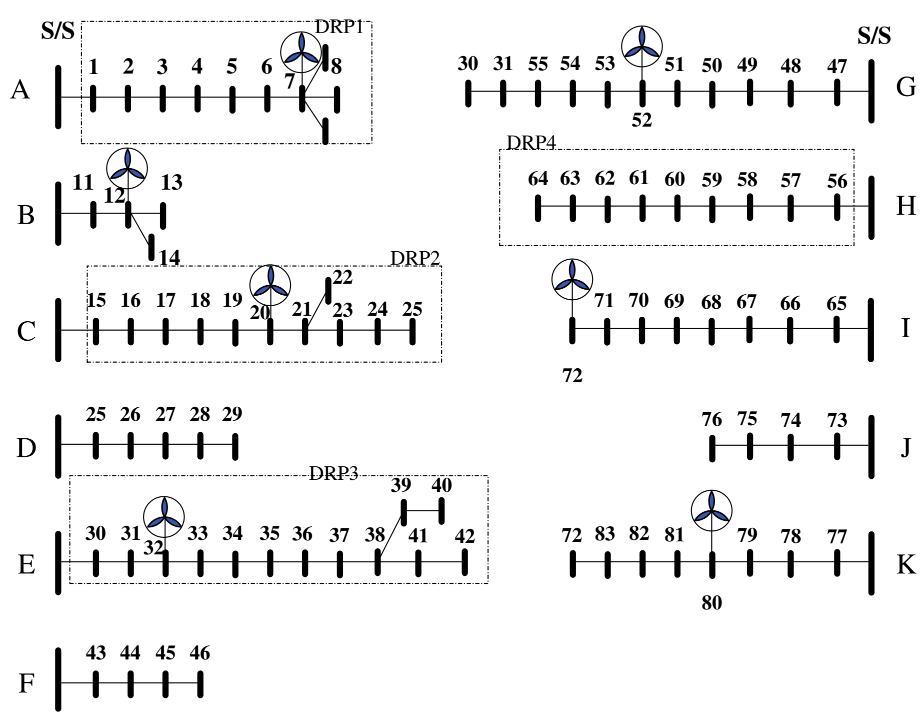

Fig. 1. 83 Bus distribution test system.

The objective function of the stochastic energy and reserve scheduling (OF^{St}) is then calculated as follows:

$$OF^{St} = CC + \sum_{s=1}^{S} \pi(s) \times SC(s) \quad (20)$$

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

The constraints of this model are described below:

- Load balance

$$P_{grid}(t) + \sum_{w=1}^{W} P_w(t) = D(t) - \sum_i DP^E(i,t) - \sum_b IL^E(b,t) \quad (21)$$

where $P_w(t)$ and $D(t)$ are the scheduled wind power of turbine w and demand in period t, respectively.

The energy balance at each scenario should also be satisfied.

$$Ps_g(s,t) + \sum_{w=1}^{W} P^t_{w,s} = P^t_{load,s} - IL^s(b,t,s) - DP^s(i,t,s) - ENS(s,t) \quad (22)$$

where $P^t_{w,s}$ and $P^t_{load,s}$ are the wind power and demand at scenario s, respectively. Also, the required load reduction from DRPs and large loads at each scenario is denoted by $DP^s(i,t,s)$ and $IL^s(b,t,s)$, respectively. $ENS(s,t)$ is the amount of involuntarily load shedding at each scenario which should be subtracted from demand.

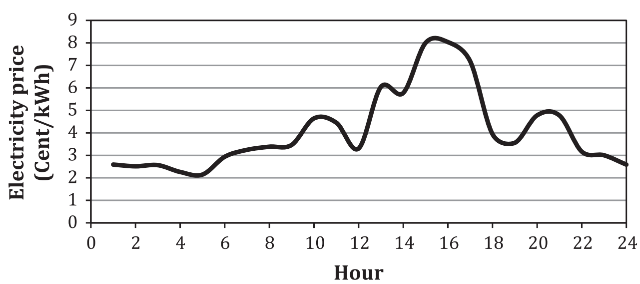

Fig. 2. Expected real-time prices of open market.

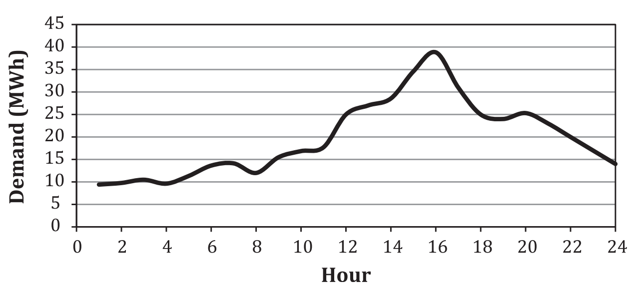

Fig. 3. Forecasted load profile of the distribution test system.

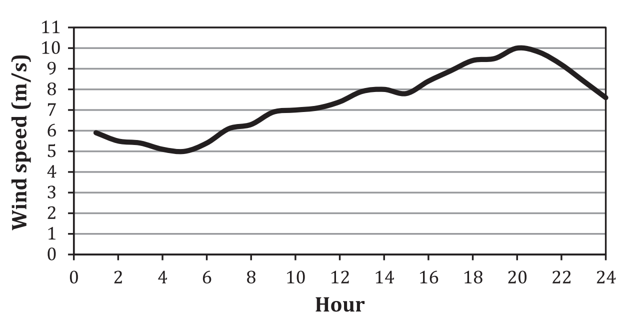

Fig. 4. Hourly wind speed forecast.

- Reserve constraint

The scheduled reserve from the main grid is determined based on the difference between the main grid scheduled power and power in each scenario. Also, the scheduled load reserve from both of DRPs ($DP^R(t)$) and individual large loads ($IL^R(t)$) is defined as the difference between amount of scheduled load reduction and load reduction in each scenario. Choosing the maximum value assures that the scheduled load reserve can cover load reduction requirements in all scenarios.

$$R_{grid}(t) \geqslant Ps_g(s,t) - P_{grid}(t) \quad \forall s,t \quad (23)$$

$$DP^R(t) \geqslant DP^s(i,t,s) - DP^E(t) \quad \forall s,t,i \quad (24)$$

$$IL^R(t) \geqslant IL^s(b,t,s) - DP^E(t) \quad \forall s,t,b \quad (25)$$

The proposed model is solved using mixed-integer Linear programming (MILP) solver Xpress [38] under GAMS [39] on a Pentium IV, 2.6 GHz processor with 4 GB of RAM.

Case study

The proposed method was applied to a modified version of the 83-bus distribution system given in [40] and illustrated in Fig. 1. The ARMA model corresponding to real-time prices and load demand are estimated through the Ontario's electricity market data from January 2012 to December 2013. The historical data of the Ontario's electricity market are available online at [41]. Thereafter, the uncertainty of next day prices is modeled via a set of 300 scenarios. The expected real-time prices of forecasted scenarios and the forecasted load profile of the test system are depicted in Figs. 2 and 3. Also, the capacity cost for spinning reserve from the main grid is considered at the rates of 25% of hourly energy price in each hour [42]. The forecasted hourly wind speed for a 24-h period is calculated from historical data measured in north part of Italy [43] and shown in Fig. 4. All wind turbines installed in the test system are of the same type with specifications power rated 1.1 MW, cut-in speed 4 m/s, nominal speed 14 m/s, and cut-out speed 25 m/s. The wind turbines are located in buses 7, 12, 20, 32, 52, 72, 80. The VOLL that is needed to estimate the social cost of interruptions was taken as 1000 \$/MW h [44].

The load buses area of each DRP is shown in Table 1. The DRPs' price–quantity offer package is presented in Table 2. It is assumed

Table 1
DRPs' support area.

DRP	Bus
DRP1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
DRP2	15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25
DRP3	30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42
DRP4	56, 57, 58, 59, 60, 61, 62, 63, 64

Table 2
Price-quantity offer package of DRPs.

	Quantity (kW)			
	Price (Cent/kW h)			
DRP1	0–200	200–600	600–1400	1400–1800
	4.9	5.8	7.9	9.1
DRP2	0–500	500–1000	1000–1500	1500–2000
	4.8	5.1	7.5	8.9
DRP3	0–100	100–400	400–900	900–1600
	5.1	5.9	7.9	9.5
DRP4	0–200	200–600	600–900	900–1700
	4.9	5.2	9.5	10.2

Table 3
Individual load offer.

IL number	Bus	Quantity (kW)	Price (Cent/kW h)
1	13	400	5.9
2	29	1100	5.0
3	72	350	7.9
4	76	1400	9.0
5	80	1000	5.1

Table 4
Stochastic and deterministic operational cost comparison.

Cost ($)	Main grid		DR		Total
	Energy	Reserve	Energy reduction	Reserve	
Stochastic	16,569	345	2233	311	19,458
Deterministic	16,569	412	2233	398	19,612

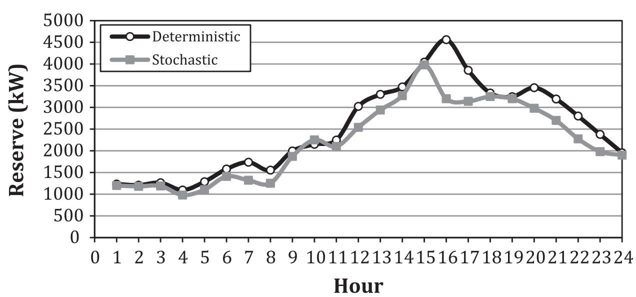

Fig. 5. The reserve requirement in the stochastic and deterministic methods.

that individual loads (IL) participating in DR program exist at buses 13, 29, 72, 76 and 80 and their offer packages are given in Table 3.

In order to show the effectiveness and capability of the proposed stochastic method, the energy and reserve scheduling has also been carried out by using the deterministic method. In the deterministic approach, the reserve requirement is determined based on the percentage of demand and renewable generation (as forecast errors) before the starting scheduling. In this case study, the demand and wind generation forecast errors are considered as 10% and 20%, respectively [5,45]. The operational costs of these two scheduling models are given in Table 4. Simulation results evidence that the stochastic scheduling model has a lower operational cost than the deterministic one due to lower reserve allocation. Wind power cost is calculated and paid to wind turbine owners after real-time operation when the real output power from these units is determined.

In the stochastic approach, real-time price, wind generation and load demand are modeled in different scenarios and their probabilistic nature is considered in the reserve allocation procedure. As a result, the scholastic model does not allocate more reserve in scenarios having low probability. The scheduled reserve provided by the main grid generators and responsive loads in the deterministic and stochastic scheduling are illustrated in Fig. 5. The results show

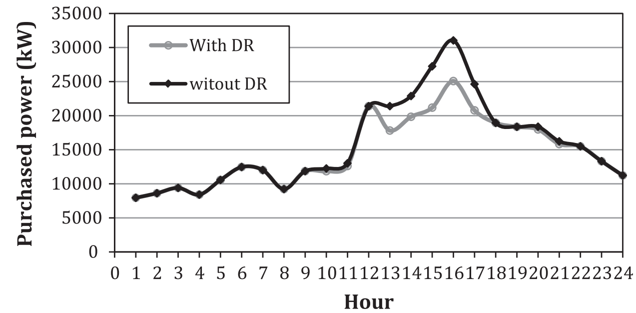

Fig. 6. Purchased energy from the main grid.

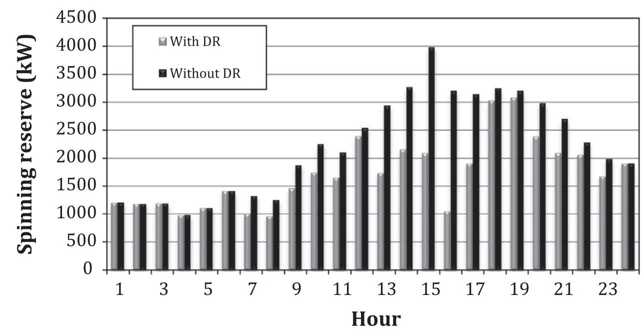

Fig. 7. Purchased spinning reserve from the main grid.

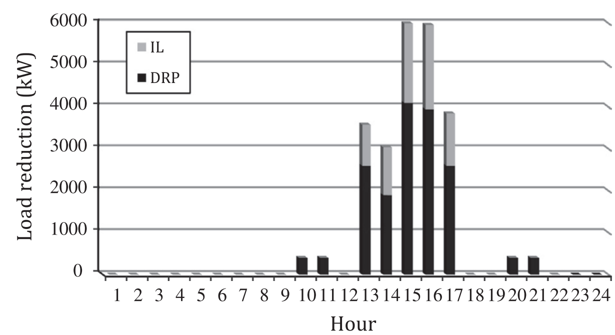

Fig. 8. Scheduled demand reduction.

that the reserve requirement in the deterministic model is higher than that in the stochastic model. Therefore, the stochastic approach allows allocating appropriate amount of reserve which causes lower operation costs.

In order to analyze the effect of the demand side participation in energy and reserve scheduling, the proposed stochastic energy and reserve scheduling is tested in two different cases: with and without considering DR programs. The operational costs of these different schedulings are given in Table 5. The costs of energy and reserve from both of the main grid and demand side are compared in these two cases. These comparison shows that the proposed model deploying DR program allows obtaining lower total operation costs.

Table 5
Scheduling costs comparison in two cases: with and without DR.

Cost ($)	Main grid		DR		Total
	Energy	Reserve	Energy reduction	Reserve	
Without DR programs	19,384	995	–	–	20,379
With DR programs	16,569	345	2233	311	19,458

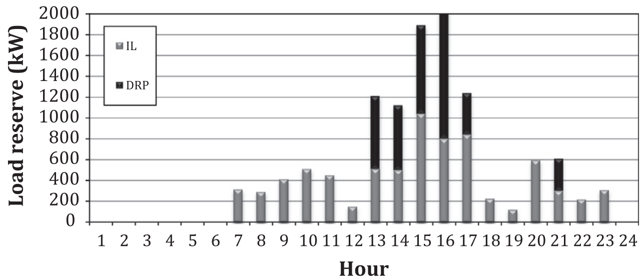

Fig. 9. Scheduled reserve from demand side.

The scheduled contracting electricity and reserve from the main gird in these two cases are shown in Figs. 6 and 7. As shown in Fig. 6, in the case with DR, the purchased energy from the main grid is reduced in hours 13–17 due to the higher electricity price. In other words, some load reduction has been contracted at these hours to reduce the operational costs. Also, comparing the purchased spinning reserve from the main grid in two cases as shown in Fig. 7, scheduled reserve provided by the main grid is reduced at some hours when the reserve price is high and the reserve is furnished by load demand reduction during these hours.

The scheduled load reduction from both individual loads (IL) and DRPs in the DR participation case is illustrated in Fig. 8. As shown in this figure, the load reduction is scheduled at hours 10, 11, 13–17, 20 and 21 in which the hourly electricity price is relatively high and the DSO prefers to purchase energy reduction from DR resources. Especially, in hours 15 and 16 when the electricity price experiences a peak, more load reductions are contracted than other hours. Also, the scheduled reserve provided by load demand participation in ancillary service demand response program is shown in Fig. 9. DR resources also provide reserve during hours in which the reserve price of the main grid is high.

Conclusion

In this paper, an energy and reserve scheduling model for distribution systems with demand side participation in energy and reserve scheduling has been proposed. A two stage stochastic approach was used to integrate the probabilistic nature of wind generation and load demand as well as the real-time price uncertainty into energy and reserve scheduling program. The results show that the loads participation in energy and reserve scheduling reduces the total operation costs. In order to show the capability of the stochastic optimization, the scheduling has been performed using conventional deterministic method and the results compared with those obtained with the stochastic method. Simulation results evidenced that the stochastic approach exhibits lower operational costs and, therefore, is more economical.

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