Chapter 14
Robust Short-Term Scheduling of Smart Distribution Systems Considering Renewable Sources and Demand Response Programs

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14.1 Introduction

The increasing growth in global energy consumption and environmental problems due to increased fossil fuel consumption has led to more interest in clean sources of energy [1]. On the other hand, the advancement of technology and reduction in the cost of carbon-free resources have accelerated the move toward usage of these technologies [2]. Among RESs, WT and solar energy have attracted more attention than other types of energy due to the uncertain nature and uncontrollability [3–5]. In addition, the potential and participation of consumers in DR programs are more advanced due to the movement of power networks to smart grids especially at the distribution level [6].

14.1.1 Problem Definition

The uncertain and uncontrollable nature of power system parameters increases the complexity and challenges of operation of SDSs and DSO such as loss of power balance, loss of reliability, and increase in operational costs. ODAS of SDSs is normally studied in short-term scheduling category. In this scheduling, 24-h prior to the implementation of the program, the production levels of different units, including WTs, DGs, and BESSs, and purchasing power from the upstream network should be

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determined. Correct and continuous operation of these networks considering RESs requires optimal scheduling. This scheduling scheme should reduce operating costs and handles the uncertainty of input parameters such as the power price of upstream grid simultaneously.

14.1.2 Literature Review

Recently, remarkable efforts have been made in the area of proposing new and realistic models for optimal scheduling of distribution networks. In [7], a two-level optimization framework for SDS scheduling has been proposed that firstly focuses on purchasing power from market, while unit commitment of DGs and interactions with the real-time market are taken in the second phase of the proposed framework. The authors in [8] used an optimal power flow algorithm to minimize the overall cost of a SDS's performance. A fuzzy-based method is proposed to plan a SDS in [9], which aims to minimize operation costs on the one hand and minimize environmental pollution on the other. Although these studies help decision-makers to gain a general view of optimization issues, they cannot show the uncertainty in real-world strategic decisions. Also, considering the absence of precise forecasting methods, a deterministic optimization method is not appropriate for the ODAS of the SDSs. Time-of-use DRPs have been investigated in optimal bidding strategy of electrical energy retailers in [10]. The authors in this study have studied the impact of system flexibility in improving the generation dispatch and reducing electricity bills for the supply and demand sections, respectively. Various modeling approaches with different strategies for fixed and flexible loads in obtaining optimal dispatch of power networks have been compared in [11]. In addition, the utilization of energy storage units and their advantages in ancillary services have been discussed in the area of improving system reliability indexes and modifying the load profile [12].

Studies in ODAS of SDSs are mainly divided into two categories including deterministic studies and stochastic studies. In the field of deterministic studies, all the inputs of the problem are entered as known values, and the outputs are determined for a given time period. For example, in the deterministic scheduling of the SDS, regardless of the probabilistic nature of the predicted variables, the reservation required by the SDS is determined prior to the planning of energy. On the other hand, in stochastic studies, non-deterministic parameters can be estimated by specific probabilistic distribution functions (PDFs), and their general purpose is to optimize the expected value of an objective function. In [13], uncertain variables related to SDS operation are modeled by PDF, and the operation is accomplished based on probabilistic scenarios. In [14], the model presented in [7] has been developed so that the expected cost of network performance is minimized and the risk associated with the uncertainties in the problem is considered in this study. However, the stochastic model presented in this reference investigates energy planning without paying attention on RESs and the risk associated with their uncertainties. The authors in [15] presented a two-level stochastic optimization model for energy and reserve planning of SDSs with the goal of minimizing the expected operating cost of the network. In [16], a two-level risk-based optimization model for SDS planning has been proposed that aims to minimize cost. The authors in [17] utilized a stochastic method for multi-objective ODAS, which aims to minimize the cost of performance and environmental pollution. In this study, consumer responsiveness is also considered as one of the sources of energy supply. The accuracy and optimality of random methods depend on the accuracy of the PDF of uncertain variables and the number of utilized scenarios in the optimization problem. The absence of proper historical data will result in an uncertain PDF of random variables and false results. In addition, with increasing in number of scenarios, the computational complexity of the optimization problem will greatly increase.

14.1.3 Novelties and Contributions

This chapter presents an optimization framework based on the concepts of robust optimization that can address the problems of both deterministic and stochastic methods. This method models random variables with uncertain PDFs and frees up the constraints. The solutions obtained from this method are safe against the worst conditions of uncertainty associated with power market price. Compared with stochastic optimization, the proposed method has several advantages. First, this method only requires the predicted values of the upper limit and the lower limit of random variables that are easier to obtain from historical data. Second, unlike stochastic methods that use probabilistic guarantees to satisfy constraints, the proposed method is followed by optimal solutions that are safe against all changes in random variables [18]. In this chapter, the SDS scheduling considering RESs is based on a mixed integer optimization. The proposed model defines the short-term operation of the network, including the amount of exchange with the upstream network and the generation of distributed resources including WTs, BESSs, and DGs. In addition through this chapter, the participation of responsive loads in network operation and their effects in minimizing the cost of network operation are studied. In addition, in order to provide a model for SDSs, the presence of DGs and RESs including WTs and BESSs, as well as DR programs, are provided in the 33-bus network. The purpose of the proposed method is to minimize the operational cost of the SDS with respect to the predicted values of upstream grid power cost. The energy and reserve scheduling of the next day should remain reliable through changing the uncertain variables of the network.

14.1.4 Chapter Organization

In Sect. 14.2, mathematical modeling including objective function and problem constraints is presented. In addition, RO method for modeling uncertainty is presented in this section. Information about the sample network is provided in Sect. 14.3.

The statistical results and charts related to the achievements of the problem are presented in Sect. 14.4. A summary of the work is presented in Sect. 14.5.

14.2 Mathematical Modeling

In this section, a complete mathematical formulation for ODAS of the smart SDS, including objective function and problem constraints, is presented. Also, modeling for RESs including WTs, DR programs, and BESSs is presented in this section.

14.2.1 The Objective Function

Energy and reserve scheduling for SDSs takes place by DSO, with the goal of minimizing the network operating costs over a 24-h period:

$$\begin{aligned} \text{Min}: & \sum_{t=1}^{24}\left\{P_{\text{grid}}(t)\times\lambda_g^E(t)\right\} \\ & +\sum_{j=1}^{N_{DG}}\left\{CE_{DG}(j,t)+CS_{DG}(j,t)+CR_{DG}(j,t)\right\} \\ & +\sum_{d=1}^{N_{\text{DRP}}}\left\{CE_{DRP}(d,t)+CR_{DRP}(d,t)\right\} \\ & +\sum_{i=1}^{N_{IL}}\left\{CE_{LL}(i,t)+CR_{LL}(i,t)\right\} \end{aligned} \tag{14.1}$$

The proposed objective function consists of four terms. The first term is the cost of supplying power and exchange with the upstream network, which is modeled as a multiplication of the hourly power purchased from the upstream network (P_{grid}) at the hourly power of the upstream network (λ_g^E). The second term refers to the costs of the DG units, including the cost of operation (CE_{DG}), the start-up cost (CS_{DG}), and the cost of the reservation provided by these units (CR_{DG}), which are subsequently introduced by Eqs. (14.6), (14.7), and (14.8), respectively. The third term relates to the cost of the DR providers, including energy costs (CE_{DRP}) and the cost of reservation (CR_{DRP}), which are introduced by Eqs. (14.24) and (14.26), respectively. The fourth term is the cost of the participation of industrial loads in DR programs including the cost of energy provision (CE_{LL}) and the cost of providing the reservation (CR_{LL}) by these units, which are modeled using Eqs. (14.28) and (14.29), respectively. The index $t = 1, \ldots, N_T$ denotes the time, the index $j = 1, \ldots, N_{DG}$ represents the DG units, the index $d = 1, \ldots, N_{DRP}$ for the DRPs, and the index $i = 1, \ldots, N_{IL}$ for the large industrial loads.

14.2.2 Constraints

The constraints associated with the ODAS of SDS including equal and unequal constraints are represented in this section.

14.2.2.1 Distribution Network Constraints

In order to ensure the safe and proper operation of the distribution network, constraints (14.2) and (14.3) are provided [19]. Equation (14.2) ensures that the voltage remains acceptable. The current range is also considered by (14.3):

$$V_{\min}(n) \leq v(n,t) \leq V_{\max}(n) \quad \forall n,t \tag{14.2}$$

$$I(m,n,t) \leq I_{\max}(m,n) \quad \forall m,n,t \tag{14.3}$$

where $V_{\min}$, $V_{\max}$, and v are the minimum, maximum, and hourly values of the bus voltages. Also, $I_{\max}$ and I are the maximum tolerable current and the hourly current of the feeder between the m and n buses, respectively.

14.2.2.2 Active and Reactive Power Balance Constraints

Reliable operation of distribution networks can be obtained by continues balance of generated power and power load demand of the network [20]. Accordingly, the following constraints should be considered for load balance at bus n at time t:

$$\begin{aligned} &P_{ug}(t) + \sum_{j\in n} P_{DG}(j,t) + \sum_{w\in n} P_{\text{Wind}}(w,t) - P_{ch}(t) + P_{dis}(t) + \sum_{i\in n} P_{LL}(i,t) \\ &+ \sum_{d\in n} P_{DRA}(d,t) - P_{\text{load}}(n,t) = V_n \sum_{n} V_{n,t}(G_{nm}\cos\delta_{n,t} + B_{nm}\sin\delta_{m,t}) \end{aligned} \tag{14.4}$$

$$\begin{aligned} &Q_{ug}(t) + \sum_{j\in n} Q_{DG}(j,t) + \sum_{w\in n} Q_{\text{Wind}}(w,t) + \sum_{d\in n} Q_{DRA}(d,t) + \sum_{i\in n} Q_{LL}(i,t) \\ &- Q_{\text{load}}(n,t) = V_{n,t} \sum_{n} V_{n,t}(G_{nm}\cos\delta_{n,t} - B_{nm}\sin\delta_{m,t}) \end{aligned} \tag{14.5}$$

where P_{Load} and Q_{Load} are the respective indicators for active and reactive power. The active and reactive power generation of each DG unit are defined by P_{DG} and Q_{DG}, respectively. P_{Wind} and Q_{Wind} are the respective active and reactive power generation of WTs. The active power charge/discharge of the storage unit is P_{ug} and P_{dis}. The reactive power charge/discharge of the storage unit is Q_{ug} and Q_{dis}. The active/reactive power reduced by large industrial load is P_{LL} and Q_{LL}. The active/reactive power reduced by DR aggregator is P_{DRA} and Q_{DRA}.

14.2.2.3 DG Units Constraints

The constraints of DG units are presented through (14.6, 14.7, 14.8, 14.9, 14.10, 14.11, 14.12, 14.13, and 14.14) [21]. The operation cost of the DG units is considered as a quadratic function of the power generated by such units, which can be stated as follows:

$$CE_{DG}(j,t) = a_j + b_j \times P_{DG}(j,t) + c_j \times {P_{DG}}^2(j,t) \quad \forall j,t \tag{14.6}$$

where the cost coefficients of the DG unit are indicated by a_j, b_j, and c_j. The start-up cost of DG units is taken into account in this study, which can be formulated as:

$$CS_{DG}(j,t) = SUC(j) \times (u(j,t) - u(j,t-1)); \qquad CS_{DG}(j,t) \geq 0; \quad \forall j,t \tag{14.7}$$

where u is a binary variable used to define the operation of DG units. The cost of providing required reserve of the network by DG units is considered as 20% of marginal price of DG units:

$$CR_{DG}(j,t) = 0.2 \times \left(b_j + 2 \times c_j \times {P_{DG}}^{\max}(j,t)\right) \quad \forall j,t \tag{14.8}$$

The power generation limits of the DG units should be considered in the scheduling of such units. Such constraint should be studied for both power and reserve scheduling of DG units, which can be stated as follows:

$${P_{DG}}^{\min}(j) \times u(j,t) \leq P_{DG}(j,t) \leq {P_{DG}}^{\max}(j) \times u(j,t) \quad \forall j,t \tag{14.9}$$

$$P_{DG}(j,t) + R_{DG}(j,t) \leq {P_{DG}}^{\max}(j) \times u(j,t) \quad \forall j,t \tag{14.10}$$

Equation (14.11) defines that the sum of power and reserve generated by DG units should be limited to maximum generation of such units. The ramp-up/ramp-down limits of the DG units can be studied using the following equations:

$$\begin{aligned} &P_{DG}(j,t) - P_{DG}(j,t-1) \leq \\ &UR(j) \times (1 - y(j,t)) + {P_{DG}}^{\min}(j) \times y(j,t) \quad \forall j,t \end{aligned} \tag{14.11}$$

$$\begin{aligned} &P_{DG}(j,t-1) - P_{DG}(j,t) \leq \\ &DR(j) \times (1 - z(j,t)) + {P_{DG}}^{\min}(j) \times z(j,t) \quad \forall j,t \end{aligned} \tag{14.12}$$

where the ramp-up/ramp-down limits of the DG units are defined by $UR(j)$ and $DR(j)$. The minimum up/down time of DG units should be considered in the scheduling of units, which can be formulated as follows:

$$\sum_{h=t}^{t+UT(j)-1} u(j,h) \geq UT(j) \times y(j,t) \quad \forall j,t \tag{14.13}$$

$$\sum_{h=t}^{t+DT(j)-1} \left(1 - u(j,h) \geq DT(j) \times z(j,t) \quad \forall j,t \tag{14.14}$$

where the respective indicators of minimum up/down time of DG units are $UT(j)$ and $DT(j)$.

14.2.2.4 Wind Turbine Modeling

The power output of WTs is considered as a function of wind speed, which is formulated as (14.15) [22]:

$$P_{wind}(t) = \begin{cases} P_r \times \dfrac{(v(t) - v_{ci})}{(v_r - v_{ci})} & v_{ci} \leq v(t) \leq v_r \\ P_r & v_r \leq v(t) \leq v_{co} \\ 0 & \text{otherwise} \end{cases} \tag{14.15}$$

where *V(t)* is wind speed, V_{ci} is cut-in speed, V_{co} is cut-out speed, and V_r is the rated speed of WT.

14.2.2.5 Modeling Battery Energy Storage System

Energy storage technology is studied in the proposed model for charging power at off-peak hours and recharging it at on-peak hours [23]. The energy balance of the storage unit is as follows:

$$SOC(b,t) = SOC(b,t-1) + \eta^{ch} \times P_{ch}(b,t) - \eta^{dis} \times P_{dis}(b,t) \tag{14.16}$$

where *SOC* is the energy storage at the storage unit. The charge/discharge efficiencies of the storage units are defined by η^{ch}/η^{dis}. The energy charged in the storage unit should be limited to its minimum and maximum values as follows:

$$\underline{SOC(b)} \leq SOC(b,t) \leq \overline{SOC(b)} \tag{14.17}$$

where the minimum and maximum energy stored in the storage unit is defined by $\underline{SOC}/\overline{SOC}$. The power charge/discharge of the storage units should be limited to its lower and upper limitations as Eqs. (14.18) and (14.19):

$$0 \leq P_{ch}(b,t) \leq \overline{P_{ch}} \times bs_c(b,t) \tag{14.18}$$

$$0 \leq P_{\text{dis}}(b,t) \leq \overline{P_{\text{dis}}} \times bs_d(b,t) \tag{14.19}$$

$$bs_c(b,t) + bs_d(b,t) \leq 1; \quad bs_c, bs_d \in \{0,1\}, \forall t \tag{14.20}$$

Equation (14.20) is used to limit the operation of storage unit in one of the charge/discharge/idle modes.

14.2.2.6 Modeling Demand Response Programs

In this chapter, consumers have been involved in DR programs in two ways. In the first way, in order to create a position for the participation of home-grown consumers or small-scale commercial and industrial consumers, two DR aggregators have been utilized. Aggregated entities examine the possibility of customer participation in DR programs, and after aggregating and integrating the responses of consumers, it is possible to connect these with the wholesale market [24]. The cost of this DR program is modeled by (14.21, 14.22, 14.23, and 14.24):

$$O_{\min}^{d} \leq o_1^d \leq O_1^d \tag{14.21}$$

$$0 \leq o_k^d \leq \left(o_{k+1}^d - o_k^d\right) \forall k = 2, 3, \ldots, k \tag{14.22}$$

$$P_{DRA}(d,t) = \sum_k o_k^d \tag{14.23}$$

$$CE_{DRA}(d,t) = \sum_k \pi_k^d \times o_k^d \tag{14.24}$$

Equation (14.21) limits the acceptance value of the load reduction by the aggregator d (o_1^d) between the minimum of decreasing value ($O_{\min}^d$) and the proposed load reduction by aggregator (O_1^d) in step 1. According to (14.22), in the other steps, the proposed acceptance of the aggregator can be between zero and proposed load reduction in the related steps. According to (14.23), the sum of the power reduced by the aggregator d at hour t (P_{DRA}) is equal to the sum of all accepted reductions in that hour. Also, the cost of reducing the load through the aggregator is calculated by (14.24), which is equal to the product of the energy reduction cost (π_k^d) in the accepted demand reduction of consumer d.

Load reduction which is not accepted by the aggregators can be utilized in reserve scheduling. In accordance with (14.25), the total amount of energy (P_{DRA}) and scheduled reserve (R_{DRA}) by decreasing the load should be limited to the maximum proposition of aggregators ($P^{\max}{}_{DRA}$). In addition, the cost of providing reserve by aggregator entities is calculated by (14.26). (KR_{DRA}) is the cost of each reservation unit provided by the aggregators:

$$P_{DRA}(d,t) + R_{DRA}(d,t) \leq P^{\max}{}_{DRA}(d,t) \tag{14.25}$$

$$CR_{DRA}(d,t) = R_{DRA}(d,t) \times KR_{DRA}(d,t) \tag{14.26}$$

The second type of DR programs which are used in this chapter is related to load reduction by large individual consumers. The power and reserve scheduling through large consumers is restricted by (14.27), and the energy and reserve costs are divided from (14.28) and (14.29):

$$P_{LL}(i,t) + R_{LL}(i,t) \le P^{\max}{}_{LL}(i,t) \tag{14.27}$$

$$CE_{LL}(i,t) = P_{LL}(i,t) \times KE_{LL}(i,t) \tag{14.28}$$

$$CR_{LL}(i,t) = R_{LL}(i,t) \times KR_{LL}(i,t) \tag{14.29}$$

In accordance with (14.27), the sum of the energy (P_{LL}) and the reserve (R_{LL}) of large industrial loads should be lower than the maximum amount of energy that can be reduced ($P^{\max}{}_{LL}$). Equation (14.28) states that the cost of reducing the energy by large consumers (CE_{LL}) is equal to the product of reduced energy (P_{LL}) at the cost of each unit of power reduction (KE_{LL}). Equation (14.29) states that the cost of providing required reserve by large consumers (CR_{IL}) is equal to the cost of the intended reservation (R_{LL}) at the intended cost for each unit of reserve scheduling (KR_{LL}).

14.2.3 The Proposed Robust Method

The robust optimization (RO) was firstly proposed by Soyster in 1973 to deal with uncertainties associated with power system parameters [25]. The RO is effective in solving the problems with a series of uncertain parameters specially when there is incomplete information on the uncertain parameters [26]. In this study, the price of power purchased from the upstream grid is considered uncertainty, which is handled using RO method. The objective function of the studied problem in (14.1), which is deterministic, can be updated as follows considering the uncertainty of price of power purchased from the upstream grid [27]:

$$\begin{aligned} &\text{Min}: \sum_{j=1}^{N_{DG}} \{CE_{DG}(j,t) + CS_{DG}(j,t) + CR_{DG}(j,t)\} \\ &+\sum_{d=1}^{N_{DRP}} \{CE_{DRP}(d,t) + CR_{DRP}(d,t)\} + \sum_{i=1}^{N_{IL}} \{CE_{IL}(i,t) + CR_{IL}(i,t)\} \\ &+\min \ \max \sum_{t=1}^{24} \left\{P_{\text{grid}}(t) \times \lambda_g^{RO,E}(t)\right\} \end{aligned} \tag{14.30}$$

where $\lambda_g^{RO,E}(t)$ is the uncertain price of upstream grid. The second term of objective function should be considered in solving the problem using the dual process.

The power price is the sum of the forecasted price and deviation of price with respect to the forecasted value:

$$
\begin{aligned}
&\max \sum_{t=1}^{24}\left\{P_{\text{grid}}(t) \times (1+z^t)\lambda_g^{\text{forecasted},E}(t)\right\} \\
&\text{subject to} \\
&z^t \le 1 \quad : \zeta^t \\
&\sum_{t=1}^{24} z^t \le \Gamma \quad : \beta \\
&z^t \ge 0
\end{aligned}
\tag{14.31}
$$

where β and ζ^t are dual variables of the problem. Γ is the robust level. The Karush Kuhn Tucker (KKT) condition can be utilized to providing the robust formulation. Accordingly, the objective function of the problem can be updated as follows:

$$
\begin{aligned}
&\text{Min} : \Gamma\beta + \sum_{t=1}^{24}\zeta^t + \sum_{t=1}^{24}\left\{P_{\text{grid}}(t) \times \lambda_g^{\text{forecasted},E}(t)\right\} \\
&+\sum_{j=1}^{N_{DG}}\{CE_{DG}(j,t) + CS_{DG}(j,t) + CR_{DG}(j,t)\} \\
&+\sum_{d=1}^{N_{DRP}}\left\{CE_{DRP}(d,t) + CR_{DRP}\left(d,t\right)\right\} + \sum_{i=1}^{N_{IL}}\left\{CE_{IL}(i,t) + CR_{IL}\left(i,t\right)\right\} \\
&\text{Constraints } (14.2) - (14.29) \\
&\zeta^t + \beta \ge \text{dev} \times \lambda_g^{\text{forecasted},E}(t) \times P_{\text{grid}}(t) \\
&\zeta^t \ge 0 \\
&\beta \ge 0
\end{aligned}
\tag{14.32}
$$

14.3 Case Study

In this chapter, the IEEE 33-bus standard network has been used to examine the effectiveness of the proposed method. Based on the results of [28], DG units are connected to the appropriate buses. Three WTs are used in this network, connected to the buses 13, 15, and 30. The rated power of WTs is 3 MW, and the cut-in, cut-out, and rated speed of these turbines are 3, 25, and 13 m/s, respectively. The prediction of wind speed over the next 24 h is shown in Fig. 14.1 [29].

Also, in the distribution network, there are four diesel generators that are connected to the buses 8, 13, 16, and 25. The coefficients for the cost of these generators and the information of the maximum and minimum power, the rate of

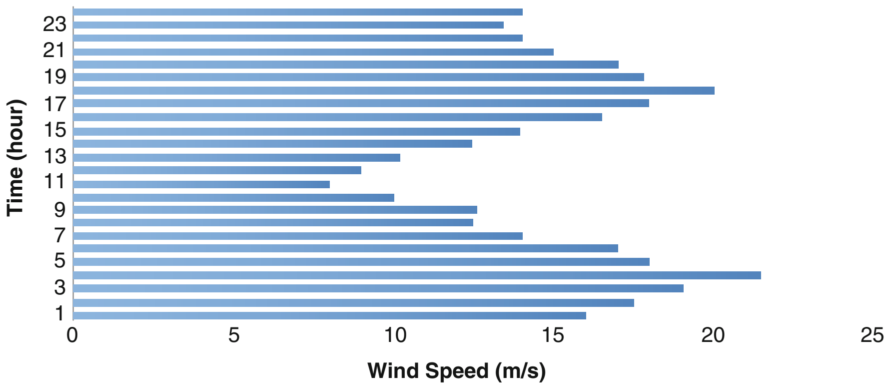

Fig. 14.1 Wind speed predicted for the next 24 h

Table 14.1 Information of DG's cost coefficients

Cost coefficients			
Units	a_i ($)	b_i ($/MWh)	c_i ($/MWh^2)
DG1	33	87	0.0025
DG2	25	87	0.0025
DG3	28	92	0.0035
DG4	26	81	0.184

power increase and power decrease, and the minimum up time and minimum down time are given in Tables 14.1 and 14.2 [30]. Also, the prediction of the hourly load during the day-ahead is shown in Fig. 14.2 [31]. Also, the 33-bus network is shown in Fig. 14.3 [32].

Also, the hourly forecast for the wholesale electricity price is assumed for day-ahead as shown in Fig. 14.4.

The battery power system with a capacity of 0.5 MW is connected to the bus 21. The minimum and maximum capacity of the energy storage system is 20% and 80% of its nominal capacity. The maximum charge and discharge rates for each hour are equal to 0.1 MW.

14.4 Results

The proposed model provides an optimal energy and reserve scheduling for distributed resources and DR programs in the studied network. Also, in order to demonstrate the effect of DR programs on the economic performance of the network, a robust ODAS has been carried out in two modes of presence and absence of DR programs, and the results have been compared.

Table 14.2 Information of the DG's technical data

Technical data					
Units	SUT ($)	MUT/MDT (h)	RU/ RD (MW/h)	Pmax (MW)	Pmin (MW)
DG1	15	2	1.8	3.5	1
DG2	25	1	1.5	3	0.75
DG3	28	1	1.5	3	0.75
DG4	26	2	1.8	4.1	1

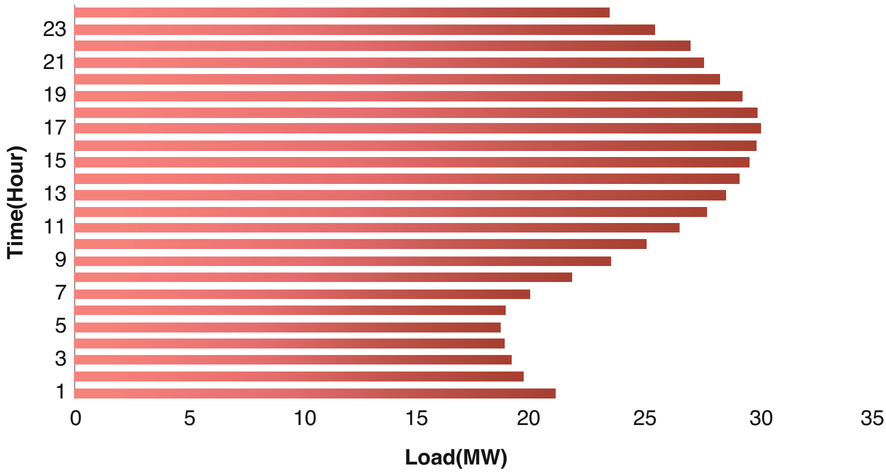

Fig. 14.2 Estimated hourly load for next 24 h

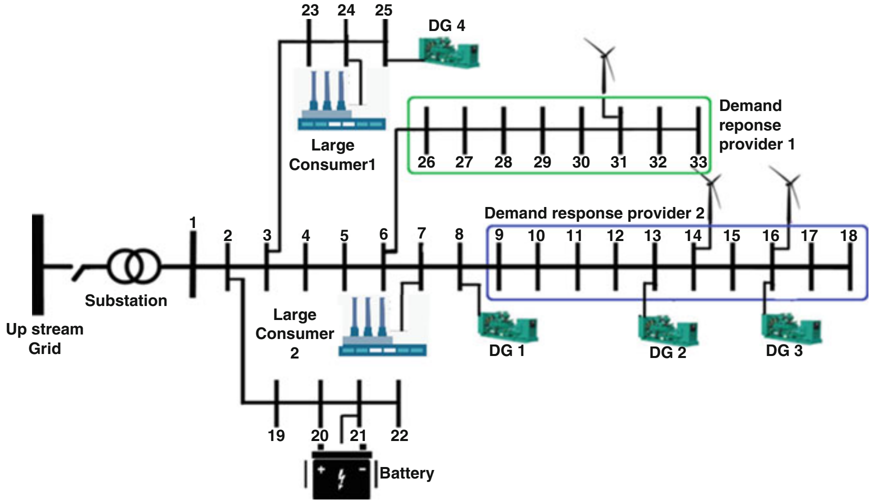

Fig. 14.3 IEEE 33-bus distribution network

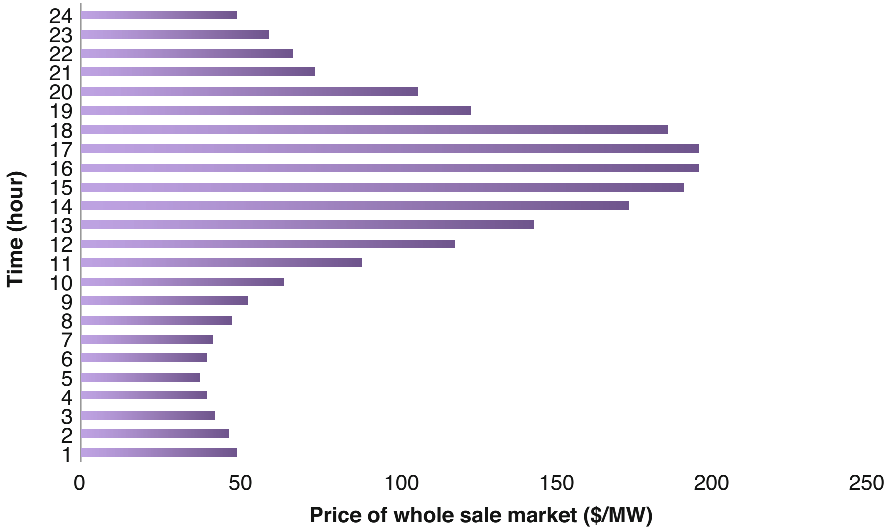

Fig. 14.4 The wholesale market price forecast for the next 24 h

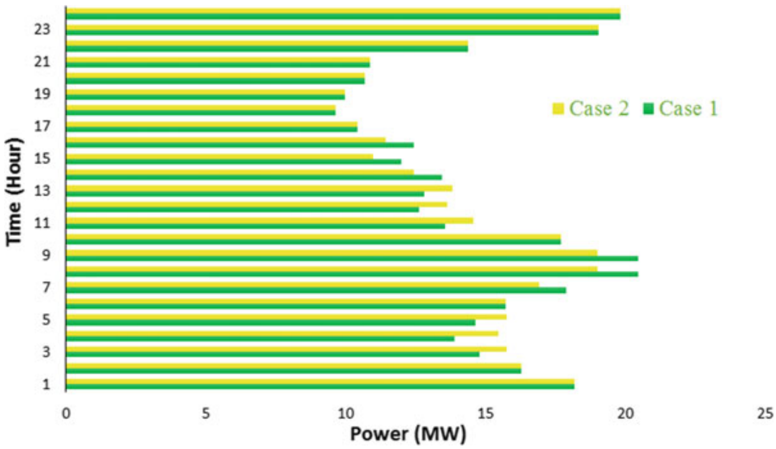

Fig. 14.5 Power scheduled to purchase from the upstream network in the next 24 h

14.4.1 First Mode (Absence of Demand Response Programs)

As seen in Fig. 14.5, during the hours when the energy price of the upstream grid is low, especially at $t = 24$ h and during the hours from 1 to 9, the required energy is purchased from the upstream grid. Also, at hours when the energy prices of DG units are lower than the wholesale market, especially during the hours from 10 to 24, the energy purchased from the upstream network is reduced. The scheduling done in this

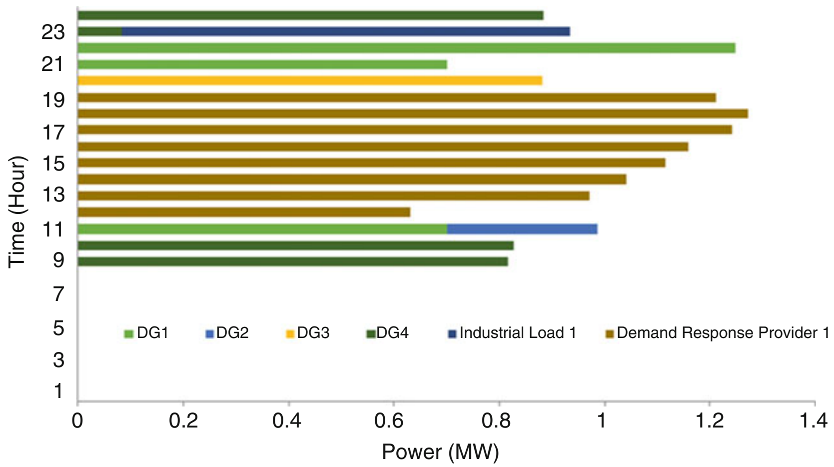

Fig. 14.6 Reservation scheduled to provide by DGs and DR programs in the next 24 h

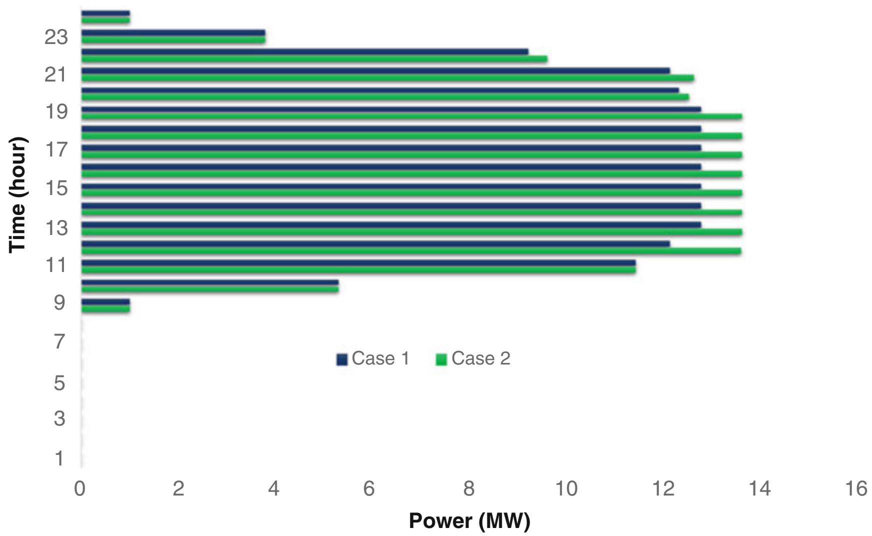

Fig. 14.7 The power scheduled to generate by DG units in the next 24 h

chapter tends to reduce the functional costs of the distribution network, and the results are more economical. As shown in Figs. 14.6 and 14.7, in the absence of DR programs, all reservations required for the distribution network are provided by DG units. It is also evident that one or more of DG units should be in standby mode at peak hours, especially times 14–21 in order to provide the required reserve capacity. Also, during the hours from 10 to 23, where the price of the wholesale market is high, it is the best time to sell the energy of the DG units, but the need to provide the required reserve would force the distribution network operator to buy energy from

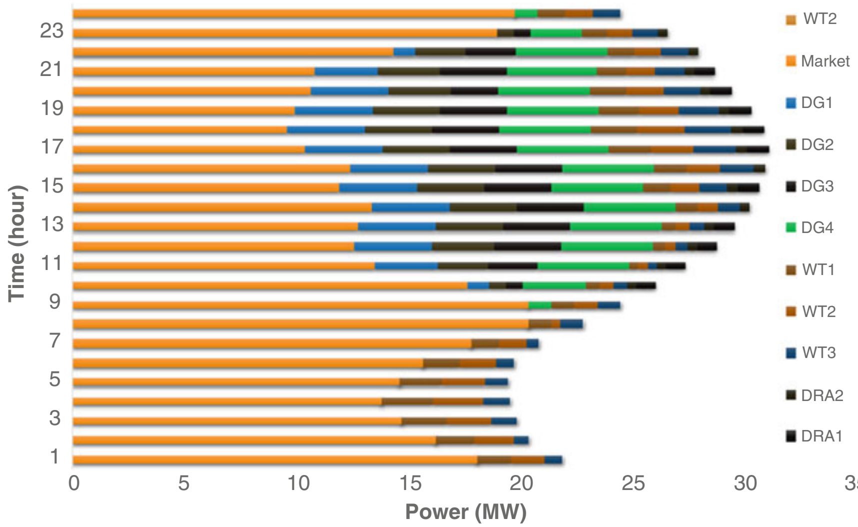

Fig. 14.8 Energy scheduled to provide by all instruments in the next 24 h

the upstream network at a higher price in the absence of DR programs. Also, at t = 1–9 and t = 24 h, when the energy price of the wholesale market is low, providing the required reserve, forces a number of DG units to remain at standby at a higher cost. As can be seen, the cost of providing reserve is increased and the operational costs of the distributed network increase.

14.4.2 Second Mode (Presence of Demand Response Programs)

In the second case, in order to demonstrate the effectiveness of DR programs, the ODAS of the SDS is taken place considering DR programs. As shown in Fig. 14.5, during the hours from $t = 10$ to $t = 23$ h, when the network upstream price is high, the reduction in consumption is taken place using DR programs by the distribution network operator. Also, the results of network reserve scheduling that is provided by DG units, DR providers, and large-scale consumer are presented in Fig. 14.6. It is also shown in Fig. 14.6 that the network DR programs meet the required reserve, and therefore as can be seen in Fig. 14.7 in case 2, DG capacity is freed up and can be fully utilized to supply the network's energy. Thus, considering load response programs, as can be seen in Figs. 14.7 and 14.8, DGs does not occupy the capacity of the DG units and can fully participate in providing the required demand of network at a lower cost.

The operation of WTs has no cost, and therefore the WTs are working in their maximum capacity of power production in both cases as can be seen in Fig. 14.9.

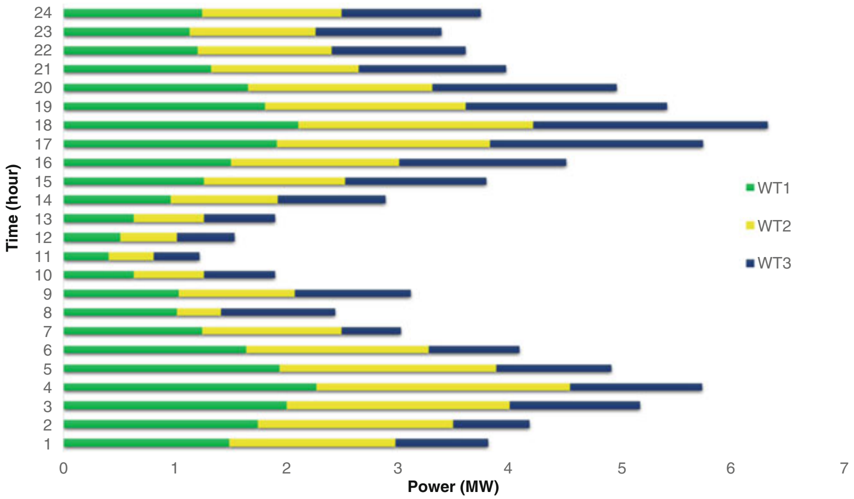

Fig. 14.9 Energy scheduled to provide by WTs in the next 24 h

14.5 Conclusions

The optimal scheduling of distribution networks considering renewable resources and DR programs has attracted much attention in recent years. In this chapter, the effect of the application of DR programs along with the presence of nonrenewable and distributed sources on optimal operation of distribution networks has been investigated. Also, a robust optimization method is used in this chapter for considering price uncertainties. This method ensures that the results will remain optimal for the worst uncertainty conditions. An IEEE 33-bus distribution network has been used to evaluate the performance of the proposed method. It also can be seen from the results that in high-priced hours, purchases from the wholesale market are reduced, and the BESS, distributed generation sources, and DR programs provide the required energy of distribution network. It can also be seen that the proposed model has the ability of ODAS of SDS. In addition, it can be seen that application of DR programs reduces the cost of network operation.

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