Chapter 11
Techno-Economic Framework for Congestion Management of Renewable Integrated Distribution Networks Through Energy Storage and Incentive-Based Demand Response Program

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Nomenclature

Sets and Indices

b	BES units index
c	CHP units index
i	Network busses index
l	Network lines index
n	WT units index
N_{B}	Set of busses
N_{BES}	Set of BES units
N_{CHP}	Set of CHP units
N_{L}	Set of lines
N_{PV}	Set of PV units
N_{WT}	Set of WT units
m	PV units index
t	Hour index

Variables

δ_i	Voltage angle of ith node
$\rho(t)$	Electricity price
$\rho_0(t)$	Primary electricity price

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θ_l	Admittance angle of lth line
$d(t)$	Consumption demand after executing DR program
$d_0(t)$	Primary consumption demand
$P_{t,l}^{\text{cap}}$	Maximum capacity of line l at time t
P_t^{DG}	Power generation of DG at tth hour
$P_{b,t}^{\text{ch}}$	The amount of charged power of bth BES at tth hour
$P_{b,t}^{\text{dis}}$	The amount of discharged power of bth BES at tth hour
P_i^{net}	Net active power of bus i
P_t^{load}	The amount of power consumption at tth hour
$P_{t,\,l}$	Active power flow of line l at tth hour
$P_{t,l}^{\text{loss}}$	Power losses of line l at tth hour
P_i^{net}	Net active power of bus i
$P_{m,t}^{\text{pv}}$	Power production of the mth PV at tth hour
P_t^{REST}	Power of net load at tth hour
$P_{n,t}^{\text{wind}}$	Power production of the nth WT at tth hour
Q_i^{net}	Net reactive power of bus i
$\text{SoC}_{b,\,t}$	State of charge of bth storage at tth hour
V_i	The amount of voltage of ith bus
Y_l	Admittance of lth line

Parameters

η_{ch}	The efficiency of charge
η_{dis}	The efficiency of discharge
Π_t^{ch}	Charging price at tth hour
Π_t^{dis}	Discharging price at tth hour
$\vec{a}$	Iteration step vector of GWO
$\vec{A}, \vec{C}$	Vectors of GWO factor
C	Scale factor of the Weibull PDF
G	Global solar radiation
$G_{\text{ING}}, G_{\text{STG}}$	Solar irradiance in standard and study condition
iter_{max}	Maximum iteration number
k	Power temperature factor
K^{DG}	Operating coefficient of DG
K^{ESS}	Operating coefficient of BES
L	Non-dominated solutions number
NOCT	Normal operating cell temperature
$P^{\text{min}}, P^{\text{max}}$	Minimum and maximum active power of DGs
P_i^{rat}	Rated power of the WT installed in bus i
P_{STG}	Rated produced power by the PV under normal trial situation
$Q^{\text{min}}, Q^{\text{max}}$	Minimum and maximum reactive power of DGs

r_1, r_2	Random vectors of GWO
s	Shape factor of the Weibull PDF
$\mathrm{SoC}_b^{\min}$	Lower bound of SoC of bth BES
$\mathrm{SoC}_b^{\max}$	Upper bound of SoC of bth BES
T_a	Ambient temperature
T_C, $T_{C,\ \mathrm{ref}}$	Cell and air temperature of PV units
v	The speed of wind
$v_{\mathrm{c\,in}}$	Cut-in speed of WT
$v_{\mathrm{c\,out}}$	Cutout speed of WT
v_{rat}	Rate speed of the WT
$V^{\min}$, $V^{\max}$	Minimum and maximum ranges of voltage magnitude
$\vec{X}$	Location of the gray wolf
$\vec{X}_P$	Location vector of the hunt
Z_i, z_i	Maximum and minimum value of the ith objective function

11.1 Introduction

11.1.1 Background

With development of the power systems and growth in the demand of electricity, the need for production and electrical energy transmission has been increased. On the other hand, with the execution of deregulation in the power sector, the optimal and economical operation of power systems has become important. Free access systems, which lead to competing in production, permit consumers to choose their energy resources voluntarily. This reason causes the maximum capacity of the lines to be used more than ever [1].

Traditionally to meet the growth in demand, new substations and distribution lines have been designed and exploited. This raises the need for further generation because of increase in system losses, as well as more costs for distribution feeders/lines and equipment. In recent decades with increasing of the oil price and other fossil fuels, which are used in power plants for electricity production, the need for economic and optimal operation of power systems increased. With regard to the problems related to the distribution lines and environmental and legal issues, it is avoided from the expansion of new lines in the distribution network (DN) as far as possible and attempted to utilize the maximum capacity of the distribution lines [2, 3].

With the ever-increasing demand and advancement in technology, the electricity market has become deregulated condition from regulated condition. Congestion, spot prices mutation, reliability reducing, and market unbalancing are some of challenges in the deregulated power market. From the above challenges, they recently focus on the congestion management (CM). Congestion occurs when distribution lines have not sufficient capacity to transfer all the power according to the market designs [4]. Congestion is defined as a line overloaded condition that causes unexpected outages, equipment failures, generators outages, a sudden increase in demand, and a lack of coordination between generation and transmission. This will prevent new contracts and the impossibility of existing contracts, causing damage to components of the system. Congestion may be partially managed by reserve units and congestion pricing and improved with some technical controls such as phase shift, change in transformer tap, reactive power control, and generation rescheduling [5].

The existence of a large number of renewable energy sources (RES) in DN increases the risk of the network capacity expansion more than ever. Therefore, the existing network expansion for congestion management leads to high investment costs in the power system. Demand response programs (DRPs) and energy storage systems (ESS) are a promising solution to deal with congestion without expansion [6].

11.1.2 Congestion in Power Systems

In the competitive power market, optimal operation in a direction that reduces costs and handles the maximum capacity of lines is very important. Participants in the power market try to gain more profit and deliver higher electrical power from distribution lines optimally. Therefore, the power systems often work near their marginal condition, and some of the lines may be overloaded, which are called congestion. Applying appropriate solutions for eliminating congestion is called CM that is one of the most important tasks of the distribution system operator (DSO). It is one of the most challenging issues in the electricity market and distribution networks [7].

11.1.3 Congestion Management in Power Systems

Recently increasing in electricity demand and preventing air contamination, it is essential to install a large capacity of RESs like solar cells, wind turbines (WT), and combined heat and power (CHP) generation systems in active distribution networks (ADN). Increasing penetration of distributed generation sources creates a series of technical problems such as overvoltage, line congestion, and harmonics, and in addition, increase in demand affects shortage of production capacity, outages, and increasing electricity prices [8].

With a steady increase in demand, additional costs are used to expand the existing DN and installation of new power stations and feeders. Thus these costs are just for power supply in some critical periods of a year. Therefore, we need to consider the appropriate methods to release the capacity of the lines, reducing network congestion during the peak hours. It is necessary to apply DRPs and ESSs to transfer the inessential load demand from peak periods to off-peak periods with the goal of CM [9].

11.1.4 Literature Review

In recent years, several methods have been used for CM in [10]. For example, author in Ref. [11] presented a formulation for coordinating both FACTS device controllers and DRPs via constrained optimization method with the goal of CM at a lower operation cost. Moreover, the incentive and penalty terms are appended to the DR mathematical model to allow the ISO through the aggregator to have two factors to control the responsive demand capacity. These terms increase the number of DR participants at certain load buses that are important for the system security. A distribution congestion price (DCP)-based market approach is suggested in [12] to investigate the behavior of DRPs on CM in distribution systems in the day-ahead electricity market. Since the DCPs should determine the accurate cost of congestion, the theory of locational marginal pricing is utilized to specify the DCPs in the day-ahead electricity market by the distribution system operator. Reference [13] has been modeled the distribution locational marginal price (DLMP) as a quadratic programming for CM in ADNs.

Paper [14] presented a novel process for specifying the optimal busses and hours for the DRP execution based on power transfer distribution coefficients, available transfer capability (ATC), and dynamic DC-OPF as well as considering the effects of DRPs on ATC and line congestion alleviation. A new CM method is presented via DRPs [15]. In this scheme, optimal combination of generation scheduling and DRPs is used to alleviate the congestion of lines. Optimal congestion management is based on electricity power market mechanism presented in [16], where DRPs are implemented with considering retailer electricity provider. The author in Ref. [17] concentrates on solving congestion problem with generation rescheduling, emergency DRPs, and direct load control (DLC). In this article, a multi-objective CM is modeled due to solve the congestion phenomena; fuzzy multi-objective PSO algorithm considering Pareto frontier is suggested. The suggested model includes a kind of objective functions and practical concepts containing maximization of transmission lines loading with operation costs as first objective and minimization of air pollution as defined second objective function. A bi-level optimization model for the accurate evaluation of ATC has been discussed in [18].

11.1.5 Contributions

Because of the presence of various distributed energy resources (DERs) in ADNs, which have various rates and generation, loads are often able to supply their required power from cheaper and more reliable sources. The load consumption of consumers has changed hourly and involves peak and off-peak hours. In peak hours, further loads enter the network and the total demand of the network increases, so in these periods, some lines become congested. The congestion of lines should be managed and reduced. For solve this problem, the available capacity of the network lines must be increased. In other words, existing lines must be expanded. This is not a good solution to solve the congestion problem because the development of the ADN has high investment cost and long-term exploitation. The proposed solution for solving the congestion problem is applied in the energy storage system (ESS) available in the ADN and demand response program (DRP). In the off-peak hours, the ESS purchase power from the upstream grid with a lower rate than the DERs and charged. Then, in the peak hours when the electricity rate is high, ESS can sell stored power to costumers, so that the congestion of lines alleviated and the operation cost minimized. Moreover, DRP manage the congestion of the system by altering the rate of electricity tariffs through different hours aimed at motivating consumers to change their energy usage patterns. The main goal of the proposed methodology is to manage the network congestion as well as minimize the operation costs with the use of ESS and DRP. This chapter attempts to provide the following contributions:

- Utilizing DR and ESS to manage the congestion and minimize the operation cost.
- Formulating the congestion problem as a cost-oriented model from the DSO perspective.
- Optimal decentralized energy management of dispatchable and non-dispatchable resources.
- Investigating the uncertainty of RESs generation using probabilistic modeling.
- Deploying a mixed integer nonlinear programming to model the problem and optimizing by gray wolf optimization (GWO) algorithm.

11.2 Problem Formulation

Equation (11.1) presents the sum of congestion and system operational cost equations, which is minimized by GWO algorithm in this chapter to reach the proposed goal include congestion and energy management of the system with implementing DR program, scheduling of BESS, and optimal planning of DERs.

$$\min F_{\text{Total}} = [F_1 + F_2] \tag{11.1}$$

11.2.1 Congestion Management

The proposed distribution network is active one and includes different kinds of private DERs. These private DERs sell their generation powers to the consumers at locational marginal prices (LMPs). But because of the limitation of the network lines capacity, some DERs with low price cannot sell their maximum production. In this case, the LMPs will be increased in some nodes of network. In order to avoid this problem, BESS is used to store excess power generated by DERs at the off-peak hours and discharged it at the peak hours in the network. In addition to BESS, the DRPs have been applied to reduce the consumption load of system in critical hours.

The goal of CM is to alleviate the distribution lines congestion or, on the other hand, to decrease the value of power flow of distribution lines which is overloaded. For this aim, the difference between the active power transactive of lines and the maximum capacity of lines should be minimized. Equation (11.2) shows the difference between active power transmission and line capacity, which is considered with a cost coefficient until the equation converted from power to cost [19]. The congestion cost coefficient (K^{Con}) for all buses is determined by the difference of LMP between the first bus and desired buses which can be calculated as shown in Eq. (11.3).

$$F_1 = \sum_{t=1}^{T} \sum_{l=1}^{N_L} \left[\left(\left| P_{t,l} - P_{t,l}^{\mathrm{cap}} \right| \right) \times K^{\mathrm{Con}} \right] \tag{11.2}$$

In this paper, the suggested CM method is implemented in accordance with the practical and technical constraints given below.

$$P_l^{\min} \le P_l \le P_l^{\max}, \quad \forall l \in N_L, \forall t \in T \tag{11.3}$$

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad \forall i \in N_{\mathrm{B}}, \forall t \in T \tag{11.4}$$

$$P_{t,l}^{\mathrm{loss}} = \left(RP_i^2 / V_i^2 \right), \quad \forall i \in N_{\mathrm{B}}, \forall t \in T \tag{11.5}$$

$$P_{t,l} = V_i \times I_l^*, \quad \forall l \in N_{\mathrm{L}}, \forall t \in T \tag{11.6}$$

$$P_i^{\mathrm{net}} = \sum_{l=1}^{N_L} \sum_{i=1}^{N_{\mathrm{bus}}} V_i V_{i+1} Y_l \cos\left(\delta_i - \delta_{i+1} - \theta_l\right), \quad \forall l \in N_{\mathrm{L}}, \forall i \in N_{\mathrm{B}}, \forall t \in T \tag{11.7}$$

Constraint (11.3) indicates the limitation of the transaction active power of the line l. Constraint (11.4) shows the minimum and maximum voltage magnitude limit of the bus i. Equation (11.5) shows the power losses of the line l at time t. The amount of power flow of lth line at tth hour is illustrated in Eq. (11.6). Equation (11.7) presents net active power of the ith bus at tth hour.

11.2.2 Operational Costs

Considering the balance between production and consumption and comparing market prices with the energy-generated price from local sources, the optimal charging/discharging scheduling of BESS is carried out. Therefore, if the output of DERs and upstream network are higher than the consumption rate, the BESS will operate as a consumer and charges. Nevertheless, if the value of DERs and upstream network are less than the amount of consumption, the BESS will act as a generator into the network and provides loads.

$$F_2 = \sum_{t=1}^{T} \left[\sum_{b=1}^{N_{\mathrm{BES}}} \left[\begin{array}{l} \left(K^{\mathrm{PV}} \times P_t^{\mathrm{PV}}\right) + \left(K^{\mathrm{WT}} \times P_t^{\mathrm{WT}}\right) + \left(K^{\mathrm{CHP}} \times P_t^{\mathrm{CHP}}\right) \\ +\left(\Pi_t^{\mathrm{Ch}} \times P_{b,t}^{\mathrm{Ch}}\right) + \left(K^{\mathrm{BES}} \times P_{b,t}^{\mathrm{Ch}}\right) + \sum_{l=1}^{N_L} \left(P_{t,l}^{\mathrm{Loss}} \times K^{\mathrm{Loss}}\right) \end{array} \right] + C^{\mathrm{DR}} \right] \tag{11.8}$$

Equation (11.8) shows the operating cost of DGs including wind power turbines, PVs, and CHP units. Optimal scheduling of ESSs, optimal production of DGs, and applied DRP could manage the congestion of lines. It should be mentioned that the cost of DRP is defined as follows and the optimal amount of incentive is determined by the GWO algorithm.

$$\begin{aligned} C^{\mathrm{DR}} = {} & (\text{Incentive cost} - \text{Reduced consumption cost}) \\ & \times \text{The amount of curtailed power by consumers} \end{aligned}$$

Different constraints are considered in the optimization problem, as shown below.

$$P_t^{\mathrm{REST}} = P_t^{\mathrm{load}} - P_t^{\mathrm{DG}}, \quad \forall t \in T \tag{11.9}$$

$$P_t^{\mathrm{DG}} = P_{n,t}^{\mathrm{WT}} + P_{m,t}^{\mathrm{PV}} + P_{c,t}^{\mathrm{CHP}}, \quad \forall t \in T \tag{11.10}$$

$$P_{t,n}^{\mathrm{WT,\,min}} \le P_{t,n}^{\mathrm{WT}} \le P_{t,n}^{\mathrm{WT,\,max}}, \quad \forall n \in N_{\mathrm{WT}}, \forall t \in T \tag{11.11}$$

$$P_{t,m}^{\mathrm{PV,\,min}} \le P_{t,m}^{\mathrm{PV}} \le P_{t,m}^{\mathrm{PV,\,max}}, \quad \forall m \in N_{\mathrm{PV}}, \forall t \in T \tag{11.12}$$

$$P_{t,c}^{\mathrm{CHP,\,min}} \le P_{t,c}^{\mathrm{CHP}} \le P_{t,c}^{\mathrm{CHP,\,max}}, \quad \forall c \in N_{\mathrm{CHP}}, \forall t \in T \tag{11.13}$$

Equations (11.9) and (11.10) show the equilibrium equation of total power and the total production capacity of DERs at time t, respectively. Additionally, constraints (11.11–11.13) express the operating zone of DERs.

11.2.3 Battery Energy Storage System

Batteries are produced from compressed cells, which turn chemical energy to electrical energy. The level of the voltage and current of the batteries are obtained from the type of parallel connection or series of cells. The batteries are classified in terms of energy and power. Efficiency, lifetime, operating temperature, discharge depth, and energy density are some of the most critical parameters of the battery.

$$\mathrm{SoC}_{b,t+1} = \mathrm{SoC}_{b,t} + \left(P_{b,t}^{\mathrm{Ch}}\eta^{\mathrm{Ch}} - P_{b,t}^{\mathrm{Dis}}/\eta^{\mathrm{Dis}}\right), \quad \forall t \in T \tag{11.14}$$

$$\mathrm{SoC}_b^{\min} \leq \mathrm{SoC}_{b,t} \leq \mathrm{SoC}_b^{\max}, \quad \forall t \in T, \forall b \in N_{\mathrm{BES}} \tag{11.15}$$

$$0 \leq P_{b,t}^{\mathrm{Ch}} \leq P_b^{\mathrm{Ch,\,max}}, \quad \forall t \in T, \forall b \in N_{\mathrm{BES}} \tag{11.16}$$

$$0 \leq P_{b,t}^{\mathrm{Dis}} \leq P_b^{\mathrm{Dis,\,max}}, \quad \forall t \in T, \forall b \in N_{\mathrm{BES}} \tag{11.17}$$

Equation (11.14) shows the SoC of battery b at tth hour. Equation (11.15) indicates the maximum and minimum limit of SoC, and constraints (11.16) and (11.17) illustrate the maximum limits of charging and discharging, respectively.

11.3 DRP Implementation

Smart grid promises high efficiency in electric energy and it is one of the major components of DRP. DR is a unique energy contract with a utility or curtailment service provider. This financial arrangement is called for load shedding, when the network is in response to the price variations. Facility managers receive a notification from an event and take the necessary measures to reduce their energy consumption. In general, DRPs can be classified in incentive-based and time-based groups, where each mentioned group includes several programs as shown in Fig. 11.1 [20–22].

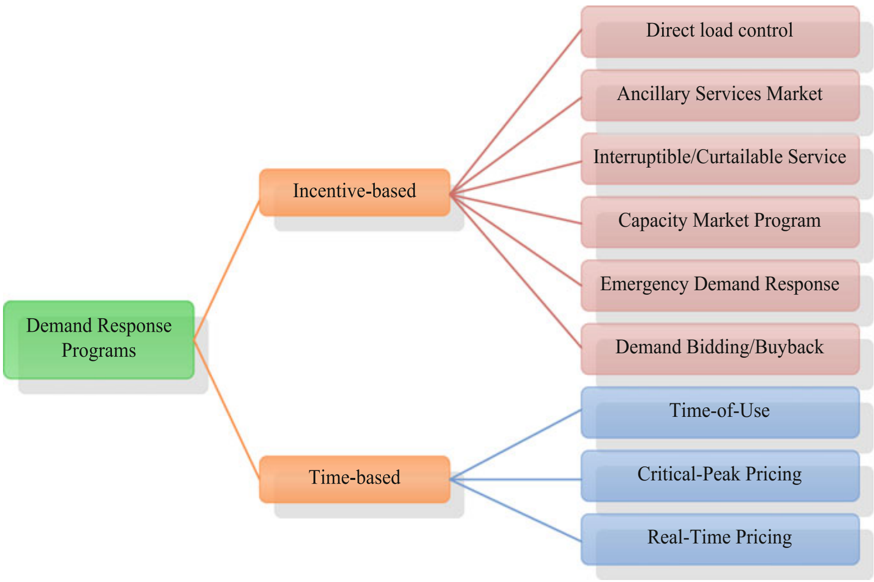

Fig. 11.1 Categories of DRPs

Elasticity is defined as the ratio of demand variation to the price variation as in (11.18) and (11.19):

$$E(t,t') = \frac{\rho_0(t')}{d_0(t)} \times \frac{\partial d(t)}{\partial \rho(t')} \tag{11.18}$$

$$\begin{cases} E(t,t') \leq 0, & \text{if} \rightarrow t = t' \\ E(t,t') \geq 0, & \text{if} \rightarrow t \neq t' \end{cases} \tag{11.19}$$

The daily amount of self-elasticity and cross-elasticity shown in (11.20) is named the price elasticity matrix.

$$\begin{bmatrix} \Delta d(1)/d_0(1) \\ \Delta d(2)/d_0(2) \\ \Delta d(3)/d_0(3) \\ \vdots \\ \Delta d(24)/d_0(24) \end{bmatrix} = \begin{bmatrix} E(1,1) & \cdots & E(1,24) \\ \vdots & \ddots & \vdots \\ E(24,1) & \cdots & E(24,24) \end{bmatrix} \times \begin{bmatrix} \Delta \rho(1)/\rho_0(1) \\ \Delta \rho(2)/\rho_0(2) \\ \Delta \rho(3)/\rho_0(3) \\ \vdots \\ \Delta \rho(24)/\rho_0(24) \end{bmatrix} \tag{11.20}$$

*J*th column from the price elasticity matrix shows the price variations. In this matrix, if the elements above the main diagonal are non-zero, it expresses that consumers want to transfer their consumption to hours other than hours at high prices. If the elements below the main diagonal are non-zero, it shows that consumers wait for hours with low price by postponing their consumption at hours with high price [14]. The net profit of consumers is presented in Eq. (11.21).

$$\mathrm{NP}(d(t)) = B(d(t)) - [d(t) \times \rho(t)] \tag{11.21}$$

The derivative of Eq. (11.21) should be zero to maximize the net profit of consumers as in (11.22).

$$\frac{\partial \mathrm{NP}(d(t))}{\partial d(t)} = \frac{\partial B(d(t))}{\partial d(t)} - \rho(t) = 0 \rightarrow \frac{\partial B(d(t))}{\partial d(t)} = \rho(t) \tag{11.22}$$

Taylor series of net profit equation is written as follows.

$$B(d(t)) = \left\{ B(d_0(t)) + \frac{\partial B(d_0(t))}{\partial d(t)}[d(t) - d_0(t)] + \frac{1}{2}\frac{\partial^2 B(d_0(t))}{\partial d^2(t)}[d(t) - d_0(t)]^2 \right\} \tag{11.23}$$

In order to reach the optimal consumption, consumers must get maximum profits as in (11.24).

$$B(d(t)) = \left\{ B(d_0(t)) + \rho_0(t)[d(t) - d_0(t)] + \frac{1}{2}\frac{\rho_0(t)}{E(t,t)d_0(t)}[d(t) - d_0(t)]^2 \right\} \tag{11.24}$$

Differentiating:

$$\frac{\partial B(d(t))}{\partial d(t)} = \rho_0(t)\left\{ 1 + \frac{d(t) - d_0(t)}{E(t,t)d_0(t)} \right\} \tag{11.25}$$

By combining (11.22) and (11.25), the single-period model is obtained as in (11.26):

$$d(t) = d_0(t)\left\{ 1 + \frac{E(t,t)[\rho(t) - \rho_0(t)]}{\rho_0(t)} \right\} \tag{11.26}$$

The multi-period model of responsive load is attained as in (11.27):

$$d(t) = d_0(t) + \sum_{\substack{t=1 \\ t' \neq t}}^{T} E(t,t') \times \frac{d_0(t)}{\rho_0(t')} \times [\rho(t') - \rho_0(t')] \tag{11.27}$$

In the end, the complete model of responsive load including the combination of the single and multi- period models is presented in Eq. (11.28).

$$d(t) = d_0(t)\left\{ 1 + E(t,t)\frac{[\rho(t) - \rho_0(t)]}{\rho_0(t)} + \sum_{\substack{t=1 \\ t' \neq t}}^{T} E(t,t')\frac{[\rho(t') - \rho_0(t')]}{\rho_0(t')} \right\} \tag{11.28}$$

11.4 Stochastic Problem Formulation

Regarding the uncertainties in load consumption, and RESs including wind and solar arrays, the scheduling of ADNs confronts with a main problem about specifying the location, capacity, and RES number. In this chapter, the uncertainties of wind, solar, and consumption load are considering applying scenario modeling. Monte Carlo simulation (MCS) is used to scenario generation for uncertain parameters [23]. The MCS is an option for modeling the behavior of the uncertain parameters that have probabilistic nature. This implies that there exists a PDF that defines the behavior of these parameters. The main theory of the MCS approach is explained below:

Assume a multi-variable function, namely, y, $y = f(x_1, \ldots, x_n)$, in which x_1 to x_n are random variables with their own PDF. The question is, knowing the PDFs of all input variables, that is, x_1 to x_n, how the PDF of y can be achieved. The theory of MCS is getting the PDF of y_e using the PDFs of input variables x_i. In the end, the PDF of the output function, y, is considered as a normal PDF with a mean and standard deviation obtained from simulations. Discrete probability distribution sets for consumption load (B_{Dl}), wind production (B_{Gw}), and solar production (B_{Gs}) are written as below:

$$\begin{aligned} &\mathrm{B}_{\mathrm{Dl}} = \left\{ \left(\mathrm{Dl}^1, \beta^1_{\mathrm{Dl}}\right), \left(\mathrm{Dl}^2, \beta^2_{\mathrm{Dl}}\right), \ldots, \left(\mathrm{Dl}^{n\mathrm{Dl}}, \beta^{n\mathrm{Dl}}_{\mathrm{Dl}}\right) \right\} \\ &\beta^1_E + \beta^2_{\mathrm{Dl}} + \cdots + \beta^{n\mathrm{Dl}}_{\mathrm{Dl}} = 1 \end{aligned} \tag{11.29}$$

$$\begin{aligned} &B_{\mathrm{Gw}} = \left\{ \left(\mathrm{Gw}^1, \beta^1_{\mathrm{Gw}}\right), \left(\mathrm{Gw}^2, \beta^2_{\mathrm{Gw}}\right), \ldots, \left(\mathrm{Gw}^n, \beta^n_{\mathrm{Gw}}\right) \right\} \\ &\beta^1_{\mathrm{Gw}} + \beta^2_{\mathrm{Gw}} + \cdots + \beta^n_{\mathrm{Gw}} = 1 \end{aligned} \tag{11.30}$$

$$\begin{aligned} &B_{\mathrm{Gs}} = \left\{ \left(\mathrm{Gs}^1, \beta^1_{\mathrm{Gs}}\right), \left(\mathrm{Gs}^2, \beta^2_{Gs}\right), \ldots, \left(\mathrm{Gs}^n, \beta^n_{\mathrm{Gs}}\right) \right\} \\ &\beta^1_{\mathrm{Gs}} + \beta^2_{\mathrm{Gs}} + \cdots + \beta^n_{\mathrm{Gs}} = 1 \end{aligned} \tag{11.31}$$

$$S = B_{\mathrm{Dl}} \cup B_{\mathrm{Gw}} \cup B_{\mathrm{Gs}} \tag{11.32}$$

$$\sum_{s \in S} \beta_{\mathrm{Dl}} \times \beta_{\mathrm{Gw}} \times \beta_{\mathrm{Gs}} = 1 \tag{11.33}$$

11.5 Providing an Overview of GWO Algorithm

In this chapter, in order to solve the suggested problem and find optimal solutions, gray wolf optimization algorithm is utilized as a new algorithm. The goal of employing this algorithm is its high convergence speed in comparison with other algorithms like genetic algorithm (GA) and particle swarm optimization algorithm (PSO). It also has great performance in convergence speed and provides better response than other optimizers. For this reason, the GWO algorithm is used in this chapter.

11.5.1 A Brief Description of GWO

GWO is a novel meta-heuristic algorithm presented in [24] and its main origin is gray wolves, which have a very dominant social hierarchy, as given in Fig. 11.2. A female and a male are chosen as the group leaders and called alpha (α). Alpha is

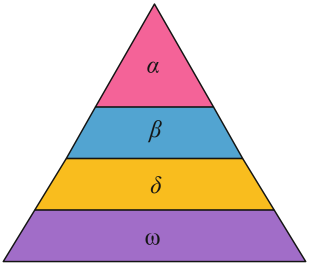

Fig. 11.2 Hierarchy of gray wolves

responsible for deciding on hunting, sleeping, and waking hours of other members. Beta (β) is the second level of the mentioned hierarchy that plays an adviser role for alpha and the best candidate to be alpha. The third and fourth level of the hierarchy are called delta (δ) and omega (ω), respectively. Omega plays the role of victim and should be obedient to other dominant wolves.

11.5.2 Mathematical Formulation of GWO Algorithm

The mathematical formulation of wolves' circling behavior through the target hunt is presented as follows.

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{\mathrm{P}}(e) - \vec{X}(e)\right| \tag{11.34}$$

$$\vec{X}(e+1) = \vec{X}_{\mathrm{P}}(e) - \vec{\mathrm{A}}.\vec{\mathrm{D}} \tag{11.35}$$

Coefficient vectors are determined as in (11.37) and (11.36).

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{11.36}$$

$$\vec{C} = 2\vec{r}_2 \tag{11.37}$$

Vector A is linearly reduced from 2 to 0 over the iteration course and r_1 and r_2 shows random vectors in [0,1]. In order to simulate the mathematical behavior of gray wolves, we suppose that alpha, beta, and delta have a better knowledge from the potential hunting position. Therefore, we save best first three answers and force the other search agents (consist of omega wolves) to update their location due to the best search agents. This description is presented mathematically as follows.

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \quad \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \quad \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{11.38}$$

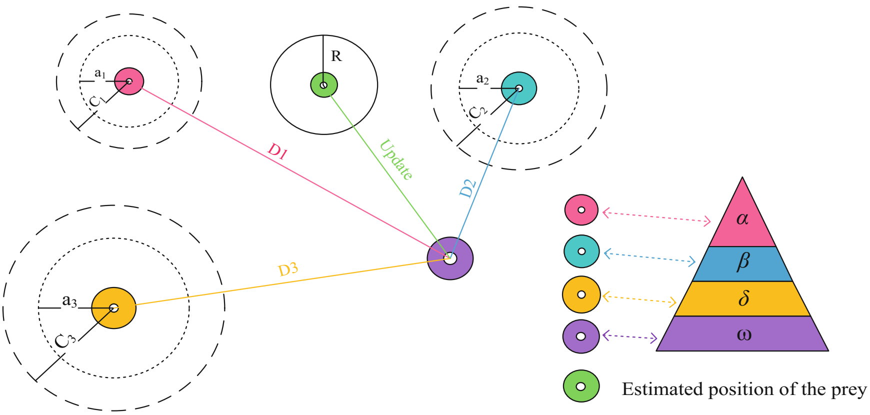

Fig. 11.3 Location updating of GWO algorithm

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \left(\vec{D}_\alpha\right), \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \left(\vec{D}_\beta\right), \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \left(\vec{D}_\delta\right) \tag{11.39}$$

$$\vec{X}(e+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{11.40}$$

Figure 11.3 explains how an agent location in a two-dimensional search region depends on the hierarchy levels. The final location got at a random position in a circle is defined due to the alpha, beta, and delta position. In other words, alpha, beta, and delta evaluate hunting positions and other wolves update their position randomly around the hunt [25].

11.6 Case Study and Simulation Results

The case study is a modified IEEE 33-bus test system. In this network, we have assumed six BESSs and six DERs. The BESS and DERs are already available in network and are being exploited. The topology of the system to implement the proposed model is shown in Fig. 11.4. BESSs and DERs data are given in Tables 11.1 and 11.2, respectively [26]. The amount of LMP at different buses of 33-bus test system has been indicated in Table 11.3. The technical data of the network is presented in Table 11.4. Figure 11.5 shows the real-time market prices or the price of energy purchased from the upstream grid.

The hourly amount of demand is shown in Fig. 11.6 with different participation factors. As seen in Fig. 11.5, the DRP increases the amount of demand in off-peak periods and reduces it in peak periods. In addition, the effects of different participation factors are displayed and compared with each other.

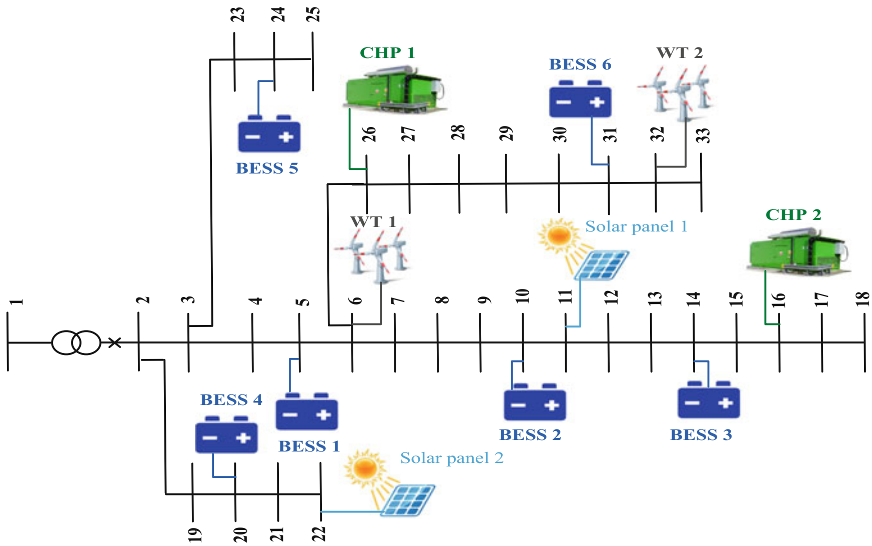

Fig. 11.4 Modified 33-bus IEEE test system with BESS and DERs

Table 11.1 Information of BESS

Number of BESS	Lower bound of SoC	Upper bound of SoC	Number of Bus	Price of charge ($/kWh)	Price of discharge ($/kWh)	η_{ch}	η_{dis}
1	150	700	5	0.10	0.20	0.90	0.90
2	100	800	10	0.15	0.22	0.90	0.90
3	150	800	14	0.10	0.20	0.75	0.75
4	100	1000	20	0.30	0.45	0.85	0.85
5	100	800	24	0.09	0.15	0.85	0.85
6	100	700	31	0.09	0.15	0.90	0.90

Table 11.2 Information of DG units

DG	Min production capacity (kWh)	Max production capacity (kWh)	Location in network	Cost coefficient ($/kWh)
1	200	600	6	0.02
2	200	500	11	0.05
3	150	450	16	0.01
4	100	400	22	0.05
5	200	700	26	0.01
6	200	600	32	0.02

Table 11.3 Amount of LMP at different buses of 33-bus test system

Bus no.	LMP ($/MVA-hr.)	Bus no.	LMP ($/MVA-hr.)	Bus no.	LMP ($/MVA-hr.)
1	20	12	22.427	23	20.674
2	20.096	13	22.66	24	20.885
3	20.559	14	22.738	25	20.992
4	20.807	15	22.796	26	21.659
5	21.056	16	22.853	27	21.739
6	21.597	17	22.925	28	22.03
7	21.671	18	22.949	29	22.239
8	21.871	19	20.111	30	22.347
9	22.106	20	20.215	31	22.495
10	22.325	21	20.234	32	22.526
11	22.362	22	20.251	33	22.534

Table 11.4 Comparison study on various approaches applied for CM problem

Ref.	Proposed method	Case study	Congestion reduction (%)
This chapter	DRP and optimal arbitrage of BESS including DERs	IEEE 33-bus system	45.43
[3]	DRP	IEEE 39-bus system	24.26
[6]	DRP along with FACT devices	IEEE 30-bus system	25.08
[7]	Rescheduling of GENCOs	IEEE 30-bus system	27.55
[10]	Rescheduling of generators along with load shedding	IEEE 118-bus system	29.41
[11]	Both DRP and distribution congestion prices	Danish 30-bus system	16.94
[13]	Rescheduling of conventional generators considering WTs	IEEE 30-bus system	31.66

The result of the BESS arbitrage is displayed in Fig. 11.7. As can be seen, the optimal charging and discharging of BESSs are determined by the proposed algorithm due to the equilibrium equation. Charging and discharging amount of BESSs depend on the production of DERs and load consumption every hour. So, if the answer of the equilibrium equation is positive, BESS is discharged. The BESSs are charged when the amount of P_{rest} is negative.

Figure 11.8 shows the optimal daily production of DERs in the presence of BESS and DRP. According to this figure, the production power of DERs depends on their capacity and location in the network, and optimal production of DERs is specified by BESS scheduling and the electricity market price in each hour. The PV units generate the power only when sun is available, i.e., 6 a.m. to 18 p.m.

In this paper, the well-known backward/forward algorithm has been used to execute power flow calculations [28]. It should be emphasized that with respect to

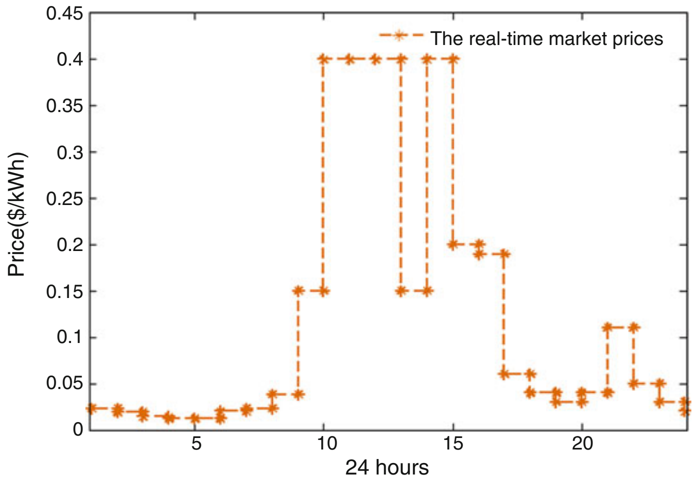

Fig. 11.5 Real-time market prices

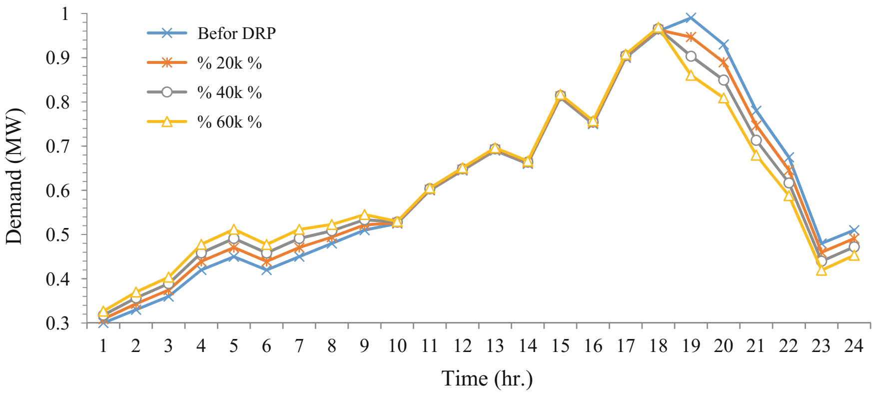

Fig. 11.6 Daily system's demand with and without DRP in different participation factors

features of proposed model which is a nonlinear, non-convex as well as non-smooth model (due to the implementation of the backward-forward load flow algorithm, considering complicating variables and constraints such as power mismatch constraints and prohibited operating zones of DER units and taking into account various objectives resulting in a NP-hard problem), it is not possible to solve it by exact methods such as CPLEX. Therefore, we had to use meta-heuristic algorithm to solve the problem. Accordingly, we studied various algorithms such as GWO, PSO, and GA, and finally with respect to obtained results, we have chosen GWO to solve the proposed congestion management problem. The optimal convergence curve obtained from GWO algorithm has been displayed in Fig. 11.9.

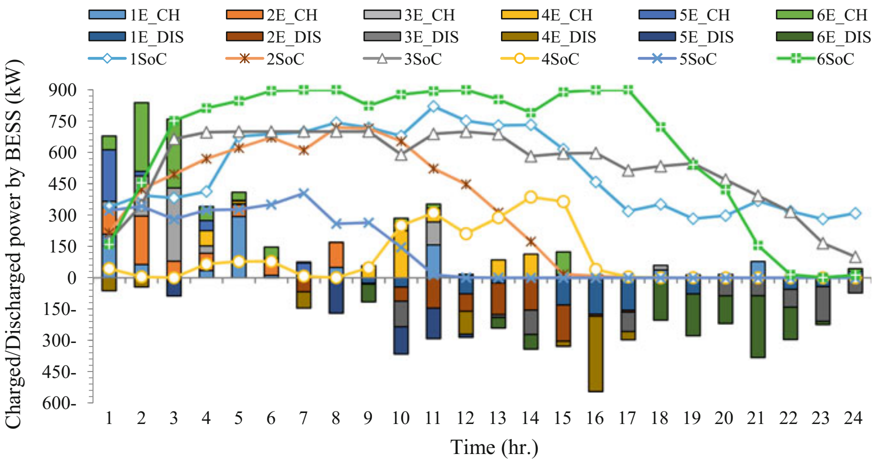

Fig. 11.7 Optimal day ahead arbitrage of BESS

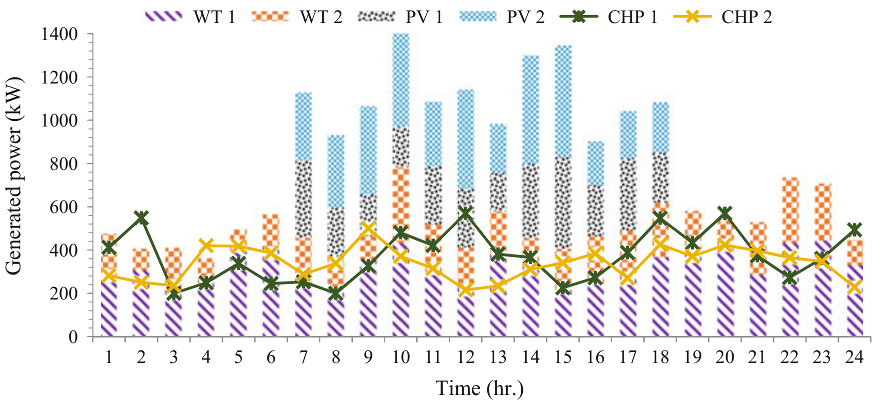

Fig. 11.8 Optimal production of DERs

The voltage profile of proposed system is presented in Fig. 11.10 in the presence of BESS, DERs, and DRP and compared with the initial case (without considering any sources). According to the figure, voltage profile of the system without considering any sources is not in acceptable range but with implementing the DRP, applying BESS, and optimal scheduling of DERs, it is limited in the allowable range. In other words, adding DRP, BESS, and DERs improve voltage profile compared with initial case. Figure 11.11 shows the 33-bus system power losses. As can be seen, the power losses of lines in the presence of the DRP have been dramatically reduced to the initial case (without DRP). In addition to the DRP, the effect of the BESS scheduling and the optimal planning of DERs is also not negligible in reducing the lines losses.

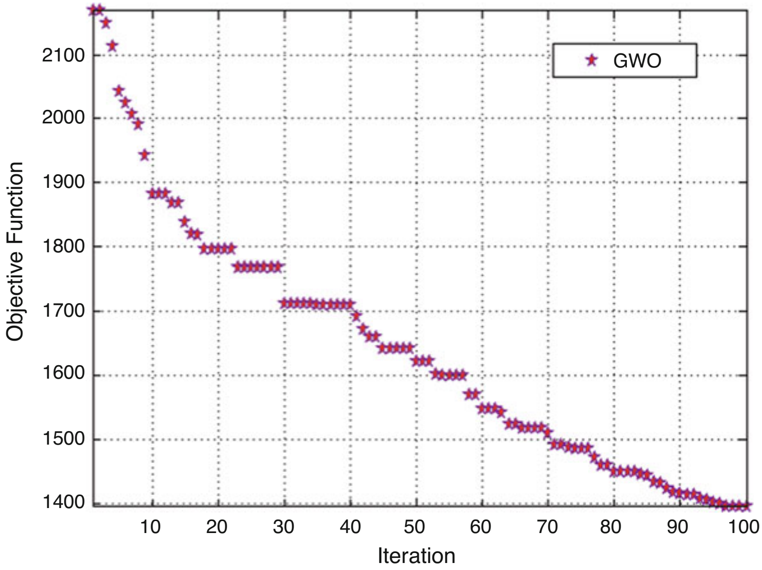

Fig. 11.9 Convergence curve obtained from GWO algorithm

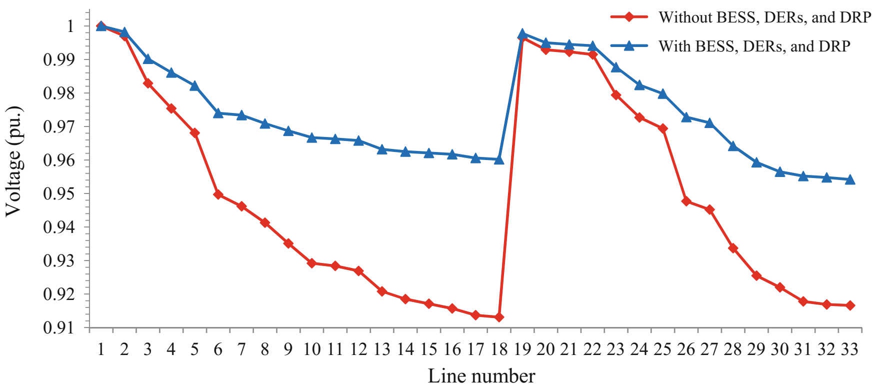

Fig. 11.10 Voltage profile of IEEE 33-bus system with and without DRP

The results of transaction powers through the lines in the presence of BESS, DERs, and DRP are illustrated in Fig. 11.12. As can be seen from the graph, the first column shows the initial transaction powers (without considering BESS, DERs, and DRP) through the lines, which is obtained from system optimal power flow, which is compared with the second column of this graph that indicates the value of power flow with proposed sources. By properly planning the DERs, optimal arbitrage of the BESS, and DRP implementation at appropriate hours, we were able to alleviate the active power flow of the lines significantly compared with the initial case (without these elements) and manage the congestion of lines as the goal of proposed problem.

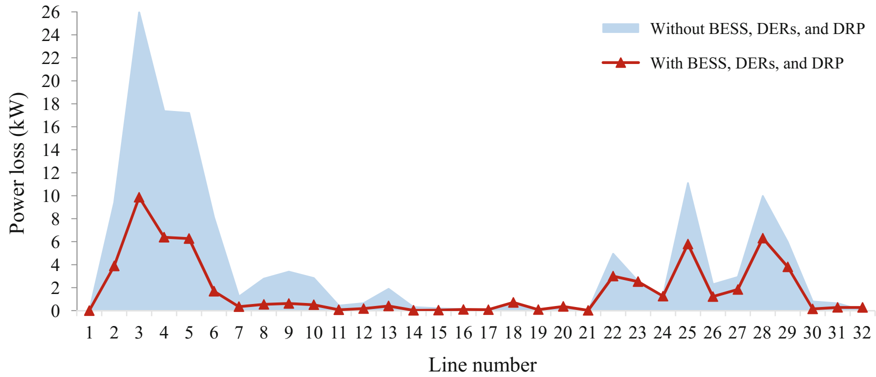

Fig. 11.11 Power losses of system with and without DRP

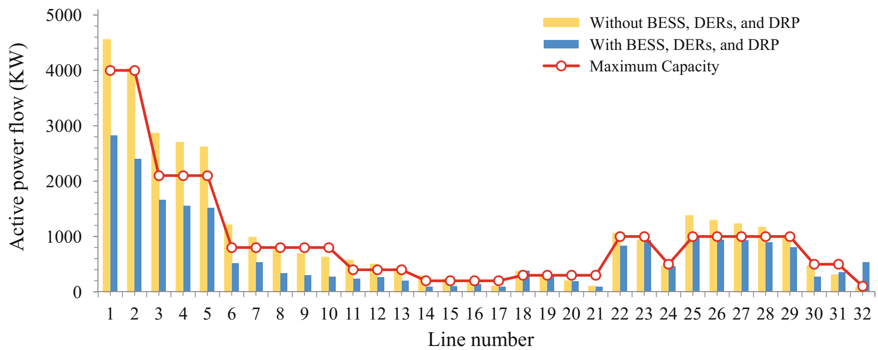

Fig. 11.12 Transaction powers through the lines in different cases

The LMP amount of each bus is presented in Fig. 11.13 and compared in two cases. As can be seen, the LMP amount in the presence of BESS, DERs, and DRP is significantly smooth compared to the initial case (without BESS, DERs, and DRP).

The amount of total active power flow (sum of all transaction powers in the lines) in the presence of DRP, BESS, and DERs with respect to the amount of total active power flow without these measures is equal to 45.43%. This value is obtained from Fig. 11.12 and written in the Table 11.4. All of the congestion reduction indexes have been calculated in the same way and compared in Table 11.4. As can be seen, DRP and optimal arbitrage of BESS along with DERs has significant effect on the congestion reduction compared to other conventional methods.

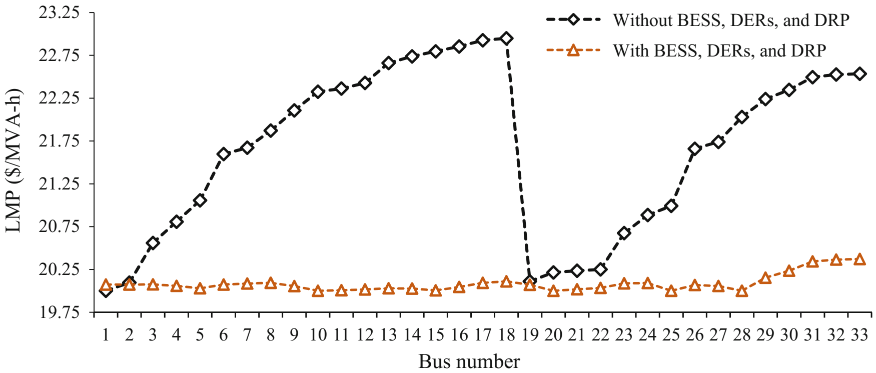

Fig. 11.13 The LMP amount at different buses

11.7 Conclusion

In this chapter, the optimal charging/discharging scheduling of BESS and incentive-based DRP execution was suggested with the goal of CM. In addition, the uncertainties pertaining to renewables were considered using the probabilistic model. Nonlinearity, non-convexity, and being non-smooth are features of the suggested problem that is why we applied the GWO algorithm to solve this problem. The arbitrage of BESS and incentive-based DRP as well as optimal production of DERs including WT, PV, and CHP systems are achieved in hourly scheduling. By utilizing the suggested method, the DSO is able to significantly decrease the overloading of lines as well as total power losses, and it can be used to improve some technical characteristic of the system like network security in dealing with overloading, voltage profile, and the network stability margin. Furthermore, results demonstrated that the BESS and DRP can decrease the curtailment energy of renewables, and it can relieve the negative impacts of uncertainties.

Appendix

The technical data of the 33-bus distribution network is given in Table 11.5.

Table 11.5 Technical data of the 33-bus test system [27] (S_{base} = 1 MVA, V_{base} = 12.66 kV)

Line no.	Sending node	Receiving node	*R* (Ohm)	*X* (Ohm)	*P* (kW)	*Q* (kVAR)
1	1	2	0.0922	0.0470	100	60
2	2	3	0.4930	0.2512	90	40
3	3	4	0.3661	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
5	5	6	0.8190	0.7070	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	0.7115	0.2351	200	100
8	8	9	1.0299	0.7400	60	20
9	9	10	1.0440	0.7400	60	20
10	10	11	0.1967	0.0651	45	30
11	11	12	0.3744	0.1298	60	35
12	12	13	1.4680	1.1549	60	35
13	13	14	0.5416	0.7129	120	80
14	14	15	0.5909	0.5260	60	10
15	15	16	0.7462	0.5449	60	20
16	16	17	1.2889	1.7210	60	20
17	17	18	0.7320	0.5739	90	40
18	2	19	0.1640	0.1565	90	40
19	19	20	1.5042	1.3555	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3084	90	50
23	23	24	0.8980	0.7091	420	200
24	24	25	0.8959	0.7071	420	200
25	6	26	0.2031	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.0589	0.9338	60	20
28	28	29	0.8043	0.7006	120	70
29	29	30	0.5074	0.2585	200	600
30	30	31	0.9745	0.9629	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.3411	0.5302	60	40

References

1. F.S. Gazijahani, J. Salehi, Game theory based profit maximization model for microgrid aggregators with presence of EDRP using information gap decision theory. IEEE Syst. J. **99**, 1–9 (2018)
2. S. Nojavan, B. Mohammadi-Ivatloo, K. Zare, Optimal bidding strategy of electricity retailers using robust optimisation approach considering time-of-use rate demand response programs under market price uncertainties. IET Gener. Transm. Distrib. **9**(4), 328–338 (2015)

3. A. Abdolahi et al., Probabilistic multi-objective arbitrage of dispersed energy storage systems for optimal congestion management of active distribution networks including solar/wind/CHP hybrid energy system. J. Renew. Sustain. Energy **10**(4), 045502 (2018)
4. A. Pillay, S.P. Karthikeyan, D.P. Kothari, Congestion management in power systems—a review. Int. J. Electr. Power Energy Syst. **70**, 83–90 (2015)
5. F.S. Gazijahani, J. Salehi, Reliability constrained two-stage optimization of multiple renewable-based microgrids incorporating critical energy peak pricing demand response program using robust optimization approach. Energy **161**, 999–1015 (2018)
6. M. Braun, Technological control capabilities of DER to provide future ancillary services. Int. J. Distrib. Energy Resour. **3**(3), 191–206 (2007)
7. P. Salyani et al., Chance constrained simultaneous optimization of substations, feeders, renewable and non-renewable distributed generations in distribution network. Electr. Power Syst. Res. **158**, 56–69 (2018)
8. F.S. Gazijahani, S. Najafi Ravadanegh, J. Salehi, Stochastic multi-objective model for optimal energy exchange optimization of networked microgrids with presence of renewable generation under risk-based strategies. ISA Trans. **73**, 100–111 (2018)
9. M. Majidi, S. Nojavan, K. Zare, Optimal stochastic short-term thermal and electrical operation of fuel cell/photovoltaic/battery/grid hybrid energy system in the presence of demand response program. Energy Convers. Manag. **144**, 132–142 (2017)
10. A. Kumar, S.C. Srivastava, S.N. Singh, Congestion management in competitive power market: A bibliographical survey. Electr. Power Syst. Res. **76**(1–3), 153–164 (2005)
11. A. Yousefi, T.T. Nguyen, H. Zareipour, O.P. Malik, Congestion management using demand response and FACTS devices. Int. J. Electr. Power Energy Syst. **37**(1), 78–85 (2012)
12. F.S. Gazijahani, J. Salehi, Robust design of microgrids with reconfigurable topology under severe uncertainty. IEEE Trans. Sustain. Energy **9**(2), 559–569 (2018)
13. S. Huang, Q. Wu, S.S. Oren, R. Li, Z. Liu, Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks. IEEE Trans. Power Syst. **30**(4), 2170–2178 (2015)
14. E. Dehnavi, H. Abdi, Determining optimal buses for implementing demand response as an effective congestion management method. IEEE Trans. Power Syst. **32**(2), 1537–1544 (2017)
15. J. Hazra, K. Das, D.P. Seetharam, Smart grid congestion management through demand response, in: *2012 IEEE Third International Conference on Smart Grid Communications* (IEEE, 2012), pp. 109–114
16. M.H. Moradi, A.R. Reisi, S.M. Hosseinian, An optimal collaborative congestion management based on implementing DR. IEEE Trans. Smart Grid. **9**(5), 5323–5334 (2018)
17. F. Zaeim-Kohan, H. Razmi, H. Doagou-Mojarrad, Multi-objective transmission congestion management considering demand response programs and generation rescheduling. Appl. Soft Comput. **70**, 169–181 (2018)
18. J. Wu, B. Zhang, Y. Jiang, Optimal day-ahead demand response contract for congestion management in the deregulated power market considering wind power. IET Gener. Transm. Distrib. **12**(4), 917–926 (2017)
19. J. Hazra, A.K. Sinha, Congestion management using multiobjective particle swarm optimization. IEEE Trans. Power Syst. **22**(4), 1726–1734 (2007)
20. B.P. Bhattarai, M. Lévesque, B. Bak-Jensen, J.R. Pillai, M. Maier, D. Tipper, K.S. Myers, Design and cosimulation of hierarchical architecture for demand response control and coordination. IEEE Trans. Ind. Informatics. **13**(4), 1806–1816 (2017)
21. F.S. Gazijahani, J. Salehi, Integrated DR and reconfiguration scheduling for optimal operation of microgrids using Hong's point estimate method. Int. J. Electr. Power Energy Syst. **99**, 481–492 (2018 Jul 31)
22. S. Nojavan, K. Zare, B. Mohammadi-Ivatloo, Optimal stochastic energy management of retailer based on selling price determination under smart grid environment in the presence of demand response program. Appl. Energy **187**, 449–464 (2017)

23. F.S. Gazijahani, J. Salehi, Optimal bi-level model for stochastic risk-based planning of microgrids under uncertainty. IEEE Trans. Ind. Informatics **14**(7), 3054–3064 (2018)
24. S. Mirjalili, S.M. Mirjalili, A. Lewis, Grey wolf optimizer. Adv. Eng. Softw. **69**, 46–61 (2014)
25. M. Shamshirband et al., Decentralized trading of plug-in electric vehicle aggregation agents for optimal energy management of smart renewable penetrated microgrids with the aim of CO_2 emission reduction. J. Clean. Prod. **200**, 622–640 (2018)
26. F.S. Gazijahani, J. Salehi, Stochastic multi-objective framework for optimal dynamic planning of interconnected microgrids. IET Renew. Power Gener. **11**(14), 1749–1759 (2017)
27. A.M. Imran, M. Kowsalya, A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using fireworks algorithm. Int. J. Electr. Power Energy Syst. **62**, 312–322 (2014)
28. S. Mehdi et al., Look-ahead risk-averse power scheduling of heterogeneous electric vehicles aggregations enabling V2G and G2V systems based on information gap decision theory. Electr. Power Syst. Res. **173**, 56–70 (2019)