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Review

Optimal dynamic economic dispatch of generation: A review

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ABSTRACT

This paper presents a review of the research of the optimal power dynamic dispatch problem. The dynamic dispatch problem differs from the static economic dispatch problem by incorporating generator ramp rate constraints. There are two different formulations of this problem in the literature. The first formulation is the optimal control dynamic dispatch (OCDD) where the power system generation has been modeled as a control system and optimization is done in the optimal control setting with respect to the ramp rates as input variables. The second one is a later formulation known as the dynamic economic dispatch (DED) where optimization is done with respect to the dispatchable powers of the committed generation units. In this paper we first outline the two formulations, then present an overview on the mathematical optimization methods, Artificial Intelligence (AI) techniques and hybrid methods used to solve the problem incorporating extended and complex objective functions or constraints. The DED problem in deregulated electricity markets is also reported.

1. Introduction

The problem of allocating the customers' load demands among the available thermal power generating units in an economic, secure and reliable way has received considerable attention since 1920 or even earlier (see the reviews in [1,2]). The problem has been formulated as a minimization problem of the fuel cost under load demand constraint and various other constraints at a certain time of interest. It has been frequently known as the static economic dispatch (SED) problem. SED can handle only a single load level at a particular time instant. However, SED may fail to deal with the large variations of the load demand due to the ramp rate limits of the generators, moreover, it does not have the look-ahead capability [3,4]. Owing to the large variation of the customers load demand and the dynamic nature of the power systems, it necessitated the investigation of optimal dynamic dispatch (ODD) problem. ODD is an extension of SED to determine the generation schedule of the committed units so as to meet the predicted load demand over a time horizon at minimum operating cost under ramp rate and other constraints. ODD has a look-ahead capability which is necessary to schedule the load beforehand so that the system can anticipate sudden changes in demand in the near future. The ramp rate constraint is a dynamic constraint which is important to maintain the life of the generators [5]. Some coupling constraints, especially ramp rate constraints, make the solution of the ODD problem more difficult than that of SED.

The first paper in the area of dynamic dispatching by Bechert and Kwatny [6] appeared in 1972 and was followed by [7–10]. In these papers the ODD problem was formulated as an optimal control problem. The optimal control dynamic dispatch (OCDD) formulation models the power system generation by means of state equations where the state variables are the electrical power outputs of the generators and the control inputs are the ramp rates of the generators. In OCDD the optimization is done with respect to the ramp rates and the solution produces an optimal output generator trajectory for a given initial generation.

Since the 1980s the ODD problem has been formulated as a minimization problem of the total cost over the dispatch period under some constraints and has been known as the dynamic economic dispatch (DED) problem [3–5,11–65]. The DED problem is normally solved by discretization of the entire dispatch period into a number of small time intervals, over which the load demand is assumed to be constant and the system is considered to be in a temporal steady state. Over each time interval a SED problem is solved under static constraints and the ramp rate constraints are enforced between the consecutive intervals [12]. In the DED problem the optimization is done with respect to the dispatchable powers of the units. Some researchers have considered the ramp rate constraints by solving SED problem interval by interval and enforcing the ramp rate constraints from one interval to the next. However, this approach can lead to suboptimal solutions [13]; moreover, it does not have the look-ahead capability.

In the ODD literature the OCDD and DED formulations have been regarded as the similar. Recently it has been shown in [66]

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that the two formulations are actually different. The similarities and deficiencies of the OCDD and DED formulations have also been addressed in [66].

The first step in the ODD formulation is to select an appropriate objective function. The following objectives have been considered: (1) minimization of the total cost (fuel cost, ramping cost, etc.) [10,14,15]; (2) minimization of the emissions (the gaseous emission such as SO_2, NO_x, CO and CO_2 produced by thermal power plants) [16–18]; (3) maximization of the profit [19,20]. The first objective is the main objective in the ODD. The second objective may be considered as a constraint and the problem is referred to as emission constrained dynamic economic dispatch [21], or may be considered as another objective where both emission and cost are minimized simultaneously and the problem is referred to as dynamic economic emission dispatch [16–18]. The third objective is used after deregulation of the electricity markets [19,20]. In the deregulated environment the generation company (GENCO) finds the optimum schedules of its energy and reserve to be sold in the market by running the DED problem with its aim to maximize its own profit (revenue minus generation cost) [19]. Sometimes, large customers are also allowed to participate in the market. In this case the independent system operator (ISO) runs the DED problem where the objective is to maximize the social profit (customer benefit minus the generation cost) [20].

The second step in the ODD problem is to determine under what constraints the problem will be solved. The following constraints have been considered in the ODD problem: load demand balance, ramp rate limits, generation capacity, spinning reserve requirement, security constraints, emission constraints, prohibited operating zone constraints, etc. Broadly, these constraints can be classified into three kinds: equality constraints, inequality constraints, and dynamic constraints. Some of these constraints such as load demand balance, and spinning reserve constraints can be modified when the DED problem is solved in the deregulated market environment.

The third step in the ODD problem is to choose a suitable optimization method which gives a global or near global optimal solution within acceptable computation time. This is actually what the majority of the ODD (especially DED) literature is devoted to. The choice of the optimization method depends on many factors, such as the type of objective function (nonlinear/linear, smooth/nonsmooth, convex/nonconvex, etc.) as well as the constraints. For smooth and convex cost functions, the ODD problem can be solved using mathematical programming-based optimization techniques. When taking into account valve-point effects or prohibited operating zones constraints, the resulting cost function is nonsmooth or nonconvex. In this case most of the mathematical optimization techniques are not suitable for solving the ODD problem. More recent works have focused on artificial intelligence (AI) methods, on par with the development of AI optimization theories. Many of AI techniques have proven their effectiveness in solving the DED problems without any or few restrictions on the shape of the cost function curves as well as constraints.

Although the development of ODD is still going on it has reached a certain level of maturity in terms of academic thought. While there are excellent surveys on SED, there is no review of the research of ODD to the best knowledge of the authors. We have structured our review as follows: (1) outlining both DED and OCDD formulations (in Section 2); (2) presenting an overview of the mathematical optimization methods, AI methods and hybrid methods that have been used for solving the ODD problem (in Section 3); (3) presenting an overview of the DED problem under emission limitations as well as DED under deregulated markets (in Section 4).

2. ODD formulation

In this section we introduce the OCDD and DED formulations. In both DED and OCDD problems, the forecast load demand is assumed to be available over the entire dispatch period $[0, NT]$ and it is given at discrete-time intervals $[kT, (k+1)T]$, $k = 0, 1, \ldots, N-1$, where T is the sampling period, N is the number of sampling periods. Most of the DED works have considered a fixed sampling period and only few papers such as [22,23] have employed a varying sampling period. In this paper we consider only a fixed sampling period. Assume that n is the number of committed generation units, L is the number of transmission lines in the network, P_i^t is the generation of unit i during the t th time interval $[(t-1)T, tT)$; $C_i(P_i^t)$ is the generation cost for unit i to produce P_i^t; D^t is the demand at time t (i.e. the t th time interval); the control variable u_i^t is the ramp rate of the unit i at time t; UR_i and DR_i are the maximum ramp up/down rates for unit i; $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum capacity of unit i, respectively; S_i^t is the spinning reserve contribution of unit i during the time interval t; SR^t is the system spinning reserve requirement for interval t; F_l^t is the active power flow through transmission line l during the interval t; $F_l^{\max}$ is the upper limit on the active power flow along line l. Let us define $\mathbf{P} = (P_1^1, P_2^1, \ldots, P_n^1, P_1^2, P_2^2, \ldots, P_n^2, \ldots, P_1^N, P_2^N, \ldots, P_n^N)$, $\mathbf{P}^0 = (P_1^0, P_2^0, \ldots, P_n^0)$, $\mathbf{u} = (u_1^0, u_2^0, \ldots, u_n^0, u_1^1, u_2^1, \ldots, u_n^1, \ldots, u_1^{N-1}, u_2^{N-1}, \ldots, u_n^{N-1})$, $\mathbf{u}^0 = (u_1^0, u_2^0, \ldots, u_n^0)$ and $\mathbf{D} = (D^1, D^2, \ldots, D^N)$.

2.1. DED formulation

The objective of DED is to determine the generation levels for the committed units which minimize the total operating cost over a dispatch period, while satisfying a set of constraints (see e.g. [3–5,11,24,25]). The DED problem is given by

$$\min C(\mathbf{P}) = \sum_{t=1}^{N}\sum_{i=1}^{n} C_i(P_i^t) \tag{1}$$

subject to

Load-generation balance:

$$\sum_{i=1}^{n} P_i^t = D^t + \mathrm{Loss}^t, \quad t = 1, 2, \ldots, N \tag{2}$$

Ramp rate limits:

$$-DR_i \cdot T \le P_i^{t+1} - P_i^t \le UR_i \cdot T, \qquad t = 1, 2, \ldots, N-1, \quad i = 1, 2, \ldots, n \tag{3}$$

Maximum capacity:

$$P_i^t + S_i^t \le P_i^{\max}, \qquad t = 1, 2, \ldots, N, \quad i = 1, 2, \ldots, n \tag{4}$$

Minimum capacity:

$$P_i^{\min} \le P_i^t, \qquad t = 1, 2, \ldots, N, \quad i = 1, 2, \ldots, n \tag{5}$$

Maximum-ramp spinning reserve contribution:

$$0 \le S_i^t \le UR_i \cdot T, \qquad t = 1, 2, \ldots, N, \quad i = 1, 2, \ldots, n \tag{6}$$

System spinning reserve requirement:

$$\sum_{i=1}^{n} S_i^t \ge SR^t, \quad t = 1, 2, \ldots, N \tag{7}$$

Line flow limits:

$$-F_l^{\max} \le F_l^t \le F_l^{\max}, \quad l = 1, 2, \ldots, L \tag{8}$$

The DED problem is usually called on the minimization of the cost function (1) under the constraints (2)–(5). To maintain system reliability and security, spinning reserve constraints (6) and (7) and security constraints (8) must be added to the DED problem. There are many ways to determine the system spinning reserve requirement. One can calculate the required spinning reserve over a time period as the size of the largest unit in operation or as a percentage of forecast load demand. Others calculate the spinning reserve requirement as a function of the probability of not having sufficient generation to meet the load [67]. Also, the system spinning reserve requirement for interval t can sometimes be given by the following equation [4,5]:

$$SR^t = \alpha_d D^t + \alpha_g \cdot \max(P_i^{\max} \text{ scheduled at time } t, \quad i = 1, 2, \ldots, N)$$

where α_d and α_g are constants which depend on the system required reliability level [4]. Besides the determination of the system spinning reserve requirement, the issue of allocation the spinning reserve among the committed units is very important (see [68] for SED and [19] for DED); however, it has received very little attention in the DED literature. The transmission line losses and the line flow can be expressed in terms of the unit outputs:

$$\text{Loss}^t = \sum_{j=1}^{n}\sum_{i=1}^{n} P_i^t B_{ij} P_j^t + \sum_{i=1}^{n} B_{i0} P_i^t + B_{00}$$

$$F_l^t = \sum_{i=1}^{n} \rho_{l,i} P_i^t$$

where B_{ij} is the ijth element of the loss coefficient square matrix, B_{i0} is the ith element of the loss coefficient vector, B_{00} is the loss coefficient constant [67], $\rho_{l,i}$ is the generalized generation distribution factors [69].

Other constraints can be added to the DED problem, when the thermal units prohibit operating zones due to the steam valve operation or vibrations in a shaft bearing [70]. The prohibited operating zone constraints can be formulated as inequality constraints as follows [26,27]:

$$\left.\begin{array}{l} P_i^{\min} \le P_i^t \le P_{i,1}^l \\ P_{i,j-1}^u \le P_i^t \le P_{i,j}^l \\ P_{i,n_i}^u \le P_i^t \le P_i^{\max} \end{array}\right\}, \qquad i \in \theta, \quad j = 2, 3, \ldots, n_i, \quad t = 1, 2, \ldots, N$$

where n_i is the number of the prohibited zones in unit i, θ is the set of units that have prohibited zones, $P_{i,j}^l, P_{i,j}^u$ are the lower and upper bounds of the jth prohibited zone.

The fuel cost functions $C_i(\cdot)$ is derived from the fuel consumption function that can be measured. The DED problem has been solved with many different forms of the cost function, such as the smooth quadratic cost function (see e.g. [4,28,12,23,29])

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2 \tag{9}$$

or the nonsmooth cost function due to the valve-point effects (see e.g. [15,30–32])

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2 + |e_i \sin(f_i(P_i^{\min} - P_i^t))| \tag{10}$$

where a_i, b_i and c_i are positive constants, and e_i and f_i are the coefficients of generator i reflecting valve-point effects. Also, a linear cost function [33,5] and piecewise linear cost function [34–36] have been employed. For smooth cost function it is usually assumed that its incremental cost function, i.e. $\mathrm{d}C_i/\mathrm{d}P_i^t$, is strictly increasing. In some power systems combined cycle units (CC) are used to supply the base load. For these units the cost function can be given as linear, piecewise or quadratic with decreasing incremental cost function [34,35]. For units with prohibited zones, the fuel cost function is discontinuous and nonconvex.

2.2. OCDD formulation

Optimal dynamic dispatch (ODD) was posed as an optimal control dynamic problem (OCDD) in [6–10]. In these papers the power system generation is modeled by means of a continuous-time control system [6–8] or as a discrete-time control system [9,10] where the state variables are the electrical outputs of the generators and the control inputs are the ramp rates of the generators. Without loss of generality, we shall consider a simple form of the OCDD problem involving three types of constraints, the load demand balance in terms of equality constraints, ramp rates in terms of dynamic constraints and generation capacity in terms of inequality constraints. The discrete-time control system is given by [9,10]:

$$P_i^{t+1} = P_i^t + Tu_i^t, \qquad t = 0, 1, \ldots, N-1, \quad i = 1, 2, \ldots, n \tag{11}$$

where u_i^t is the ramping action of unit i at time t. The equations in (11) actually define a coordinate transformation between the variables P_i^t and the variables u_i^j. It is obvious that the inverse coordinate transformation is given by

$$P_i^t = P_i^0 + \sum_{j=0}^{t-1} Tu_i^j, \quad t = 1, 2, \ldots, N \tag{12}$$

The OCDD problem is formulated as follows: given a set of generators, load demand $\mathbf{D}$ and initial generation $\mathbf{P}^0$, find a control action $\mathbf{u}$ to minimize the total generation cost and to meet the load demand of a power system over the dispatch period:

$$\min C(\mathbf{P}^0, \mathbf{u}) = \sum_{t=1}^{N}\sum_{i=1}^{n} C_i\left(P_i^0 + \sum_{j=0}^{t-1} Tu_i^j\right) \tag{13}$$

subject to the constraints

$$\sum_{i=1}^{n}\left(P_i^0 + \sum_{j=0}^{t-1} Tu_i^j\right) = D^t, \quad t = 1, 2, \ldots, N \tag{14}$$

$$-DR_i \le u_i^t \le UR_i, \qquad t = 0, 1, 2, \ldots, N-1, \quad i = 1, 2, \ldots, n \tag{15}$$

$$P_i^{\min} \le P_i^0 + \sum_{j=0}^{t-1} Tu_i^j \le P_i^{\max}, \qquad t = 1, 2, \ldots, N, \quad i = 1, 2, \ldots, n \tag{16}$$

When the OCDD problem is solvable, it gives an open-loop optimal controller denoted by $\bar{\mathbf{u}} = (\bar{u}_1^0, \bar{u}_2^0, \ldots, \bar{u}_n^0, \bar{u}_1^1, \bar{u}_2^1, \ldots, \bar{u}_n^1, \ldots, \bar{u}_1^{N-1}, \bar{u}_2^{N-1}, \ldots, \bar{u}_n^{N-1})$ and the corresponding optimal generation is given by $\bar{\mathbf{P}} = (\bar{P}_1^1, \bar{P}_2^1, \ldots, \bar{P}_n^1, \bar{P}_1^2, \bar{P}_2^2, \ldots, \bar{P}_n^2, \ldots, \bar{P}_1^N, \bar{P}_2^N, \ldots, \bar{P}_n^N)$, where $\bar{P}_i^t = P_i^0 + \sum_{j=0}^{t-1} T\bar{u}_i^j$, $t = 1, 2, \ldots, N$.

The OCDD and DED formulations have many similarities. For example, both of them are subject to similar sets of constraints, and the solutions are to be implemented repeatedly and periodically due to the cyclic consumption behavior and seasonal changes of the demand. Exactly due to this periodic implementation, both formulations have the same technical deficiencies as illustrated in [66]. Furthermore, it is shown in [66] that the two formulations are actually different. The differences between OCDD and DED are listed below:

(1) The OCDD formulation produces an optimal solution for a given initial value $\mathbf{P}^0$ and the optimal solution also depends on $\mathbf{P}^0$ while the DED problem does not consider the initial generation $\mathbf{P}^0$ and is totally independent of $\mathbf{P}^0$.
(2) The OCDD formulation has the ramp limit for $\mathbf{u}^0$, that is, the differences between P_i^1 and P_i^0 must satisfy the ramp constraints; however, the DED formulation considers the ramp rate constraints only for $P_i^2 - P_i^1, P_i^3 - P_i^2, \ldots, P_i^N - P_i^{N-1}$ and has ignored the ramp limit for $P_i^1 - P_i^0$, where $i = 1, \ldots, n$.

The OCDD problem was originally described in [6,7]. In these papers, necessary conditions for the optimal controller are obtained for an arbitrary number of generators. The optimal feedback controller was synthesized only for the special case of two generators sharing load owing to computational problems. Bechert and Chen [8] proposed a multi-pass dynamic programming approach to solve the OCDD problem and obtained the optimal generator output trajectories for up to five generators. The proposed algorithm finds only a local optimum schedule and the computer memory and calculation time requirements increase exponentially with the number of generators. The main drawback of the approaches proposed in [6–8] has been dimensionality limitation.

In 1980 Ross and Kim [9] proposed a successive approximation approach with dynamic programming for solving the OCDD problem without limitation of the number of units. The valve-point effects is considered. The large problem with ramping constraints is broken down into smaller subproblems. Each subproblem pairs one unit with an artificial unit and is solved via dynamic programming by discretizing the generation outputs. The feasibility of the problem has been demonstrated on a problem involving 15 units and 16 intervals. However, execution time and problem size increase almost exponentially with the number of units.

In 1998 the OCDD problem was revisited again by Travers and Kaye [10]. They applied constructive dynamic programming to solve the OCDD problem. Both the generation cost and the ramping cost are included in the objective function as piecewise linear functions. The proposed method provides optimal trajectories for all system states from all times without the need to discretize generator output. However, the dynamic programming method suffers from the “curse of dimensionality”.

The open-loop nature of the optimal solution of the ODD problem would not allow to compensate for inaccuracies originating from modeling uncertainties, external disturbances and unexpected reactions of some of the power system components. Therefore a closed-loop optimal solution is needed. The approaches given in [6–10] can generate closed-loop solutions but it suffers from the above mentioned drawbacks. In [66], a feedback controller is designed by means of model predictive control (MPC) method based upon the OCDD framework. It is shown theoretically that the closed-loop MPC solutions asymptotically approach the optimal solution of an extended version of the DED problem. The robustness of the MPC algorithm is also shown.

3. Literature review on DED

Since the dynamic dispatch problem was formulated as a DED problem, the thrust of research has focused on various optimization techniques and procedures incorporating extended and complex constraints. These optimization techniques can be classified into three main categories. The first category is mathematical programming-based or heuristically-based, such as the lambda iterative method [3], gradient projection method [23], Lagrange relaxation [37], linear programming [4], nonlinear programming [14], interior point methods [11,36,5], dynamic programming [38], etc. The advantages of these methods including: optimality is mathematically proven in some algorithms [71]; they can be applied to large-scale problems [71]; they have no problem-specific parameters to specify [72]; moreover, some of these methods are computationally fast. However, these methods can converge to a local optimum and are sensitive to the initial starting points [39,73]. Many of these techniques are not applicable to a certain class of cost functions; for example lambda-iterative, Lagrange relaxation and gradient technique methods, etc. when used to solve DED with nonsmooth or nonconvex cost functions, can fail to get global optimal solutions [31]. For non-monotonically increasing incremental cost functions, the lambda iterative method may not result in the optimal solution [35]. Linear programming usually faces poor computation efficiency [40]. Dynamic programming can solve DED problems with nonsmooth cost functions [38]; however, it suffers from the “curse of dimensionality” and local optimality [12,73].

The second category is the methods based on artificial intelligence, such as artificial neural networks [28,40] and stochastic optimization methods such as genetic algorithm (GA) [33], simulated annealing (SA) [41], evolutionary programming (EP) [42], differential evolution (DE) [43,44], particle swarm optimization (PSO) [26,39,45] and Hopfield neural network (HNN) that have been successfully used for solving the DED problem. Artificial neural networks such as HNN have been found to generate a high quality solution for the DED problems with smooth cost functions [40,28]. Stochastic optimization methods can solve DED without any or fewer restrictions on the shape of the cost function curves due to their ability to seek the global optimal solution. Moreover, these algorithms do not depend on the first and second differentials of the objective function. However, the AI techniques suffer from the drawbacks of the long computation time [74] and the large number of arbitrary or problem-specific parameters [72].

The third category is the hybrid methods, which combine two or more techniques previously mentioned in order to get best features in each algorithm. These methods such as evolutionary programming with sequential quadratic programming (EP-SQP) [15], particle swarm optimization with sequential quadratic programming (PSO-SQP) [30,31], Hopfield neural network with quadratic programming (HNN-QP), [46], EP-PSO-SQP [27] have proven their effectiveness in solving the DED problems.

In this section, we concentrate our review on the works that deal with the DED problem where the optimization is performed over the whole dispatch period (e.g. 24 h) under the ramp rate constraints and other constraints mentioned in the previous section. However, there are several works that solve the SED problem over a single interval while taking into account the ramp rate between the current interval and previous one (see, for example, from the literature we mention here but a few [72,73,75–78]). This approach can be implemented interval-by-interval within the dispatch period; however, it may produce suboptimal solutions [13].

3.1. DED with mathematical programming-based techniques

The previous OCDD and DED formulations with the three basic constraints, load demand balance, ramp rate and generation capacity constraints can be put into the following general form:

$$\begin{aligned} &\min && f(x) \\ &\text{subject to} && g_i(x) = 0, \quad i = 1, 2, \ldots N \\ &&& h_j(x) \le 0, \quad j = 1, 2, \ldots M \end{aligned} \tag{17}$$

where M is the number of inequality constraints and x is vector of size nN.

The above optimization problem can be solved by several approaches depending on the shape of the objective function. Some approaches are based on transforming the constrained problem to a parameterized sequence of unconstrained problems by using a penalty function for the constraints. Using an iterative process, the solution of the unconstrained problem converges to the constrained one [74]. Other approaches such as SQP and interior point (IP) methods are based on the solution of the Karush–Kuhn–Tuker (KKT) equations by forming a Lagrange function as [74,67]:

$$L(x, \lambda, \mu) = f(x) + \sum_{i=1}^{N} \lambda_i g_i(x) + \sum_{j=1}^{M} \mu_j h_j(x) \tag{18}$$

where λ_i, and μ_j are the Lagrange multipliers. By computing the derivative of the Lagrange function with respect to the variables x, λ_i, and μ_j, the resulting KKT necessary conditions for (18) are given by

$$\begin{aligned} &\frac{\partial L}{\partial x_i} = 0, \quad i = 1, 2, \ldots, N \\ &\frac{\partial L}{\partial \lambda_i} = g_i(x) = 0, \quad i = 1, 2, \ldots, N \\ &\frac{\partial L}{\partial \mu_j} = h_j(x) \leq 0, \quad j = 1, 2, \ldots, M \end{aligned} \tag{19}$$

$$\mu_j h_j(x) = 0 \quad \text{and} \quad \mu_j \geq 0, \qquad j = 1, 2, \ldots, M \tag{20}$$

If f, g, and h are convex functions, then the KKT equations are both necessary and sufficient for a global optimal solution.

Inequality constraints can also be converted into equality constraints by adding slack variables as follows:

$$h_j(x) + s_j^2 = 0, \quad j = 1, 2, \ldots, M$$

and then the Lagrange function will depend on the variables x, λ_i, s_j and μ_j. The KKT conditions are obtained by computing the derivative of the Lagrange function with respect to the variables x, λ_i, s_j and μ_j.

The Lagrange relaxation method for the constrained optimization problem is based on appending the complicated constraints to the objective function after multiplying them by Lagrange multipliers. Assume that there are some inequality constraints that make the problem relatively easy to solve if it is removed, then problem (17) can be rewritten by splitting the inequality constraints as follows:

$$\min_x f(x) \tag{21}$$

$$g_i(x) = 0, \quad i = 1, 2, \ldots, N \tag{22}$$

$$h_j(x) \leq 0, \quad j = 1, 2, \ldots, M^* \tag{23}$$

$$h_j(x) \leq 0, \quad j = M^* + 1, \ldots, M \tag{24}$$

where constraints (24) represent the complicated constraints in the problem. The Lagrange function can be written as

$$L(x, \mu) = f(x) + \sum_{j=M^*+1}^{M} \mu_j h_j(x)$$

Then the dual function is defined by

$$\begin{aligned} &D(\mu) = \min_x L(x, \mu) \\ &g_i(x) = 0, \quad i = 1, 2, \ldots, N \\ &h_j(x) \leq 0, \quad j = 1, 2, \ldots, M^* \end{aligned}$$

It is clear that the dual function constitutes a lower bound on the value of the objective function $f(x)$. The dual problem is formulated as

$$\max_\mu D(\mu) = \max_\mu (\min_x L(x, \mu)) \tag{25}$$

The dual problem (25) is solved by an iterative process, e.g. by the subgradient method to update the multipliers μ and at the final the optimal solution is obtained. For convex optimization problems, the solution obtained by the dual problem (25) and the primal problem (17) are the same. While for nonconvex optimization problems there is a duality gap between the solutions obtained by (25) and (17).

Some early works propose a heuristic technique for solving the DED problem. This technique works by dividing the DED problem into SED problems that are solved backward in time [3,47]. At each time interval, the SED problem is solved and the unit operating limits have to be updated. Here, the ramp rate limits are included in the unit operating limits. Wood [3] considered the spinning reserve constraints as well as the transmission losses while Isoda [47] did not. The difference between the algorithms used by Wood and Isoda is in the way Isoda determined the unit operating limits in each SED problem. If the load demand balance was not satisfied in the first interval, Isoda proposed to move forward in time while adjusting the operating limits interval after interval until the load balance is satisfied in all intervals. The proposed heuristic technique in [3,47] produces suboptimal solution.

Since the ramp rate constraints couple the time intervals, the DED problem is a difficult optimization problem. If the ramp rate constraints are relaxed, the DED problem can be reduced to a set of uncoupled SED problems that can easily be solved. This can be done by adding a penalty function derived from the ramp rate constraints to the objective function [24]. In this case, the DED problem is transformed into a SED problem. In [24] a gradient projection method with conjugate search directions is proposed to solve the resulting SED problem. Wang and Shahidehpour [48] included in the objective function a term representing the reduction in the life of the turbine caused by excessive ramp rates. The DED problem was solved by linear programming.

Muki et al. [49] formulated a dual optimization problem by appending the load balance constraints to the objective function after multiplying them by Lagrange multipliers. Then the problem is decomposed into subproblems, each of which concerns one generator and it is solved under the remaining constraints. The dual problem is solved iteratively to update the Lagrange multipliers and obtain the optimal solution.

The feasibility and optimality of the solution of the DED problem are only realized in more recent studies [14,79]. Han et al. [14] examined the factors that affect the feasibility and optimality of the solutions to the DED problem. According to the idea of coupling, two methods are proposed. The first is guaranteed to find a feasible solution and the second is an efficient technique for finding the optimal solution.

For system security, line flow limits must be considered in the DED problem to prevent transmission lines from being overloaded. The security constrained DED problem has been solved by several techniques. Some are based on the constrained-relaxation [13,37,50], interior point (IP) methods [11,36,5], redispatch technique [4], gradient projection method [23], and other algorithms [25,51,22].

Based on the constrained-relaxation technique, Irving and Sterling [50] employed a dual revised simplex algorithm for solving the DED problem with security and spinning reserve constraints. Hindi and Ghani [13] developed the formulation given in [50] and proposed a solution algorithm based on a Dantzig-Wolfe decomposition, which yielded a capacitated transshipment subproblem (without security and spinning reserve constraints) along with a master problem solved by the revised simplex method.

The Lagrange relaxation method has been used to solve the DED problem with security and spinning reserve constraints in [37]. The coupling constraints are relaxed and the resulting problem is decomposed into a number of subproblems corresponding to the intervals in the dispatch period. The subproblems are solved by a priority list technique. Lagrange multipliers are updated by subgradient optimization. If a solution is not deemed sufficiently close to the optimal, a Dantzig-Wolfe decomposition is invoked to find a solution to the primal problem.

IP methods are a certain class of algorithms to solve linear and nonlinear convex optimization problems. Contrary to the simplex method, IP reaches an optimal solution by traversing the interior of the feasible region. Several variants of the IP method with its application in power systems have been reported in [80]. For the security-constrained DED problem, IP methods such as quadratic IP [11], homogeneous IP [36] and linear IP [5] have been employed. In [11,36] the DED problem is converted into a single optimization problem by moving all the constraints to the objective function after adding slack variables to the inequality constraints. In [11] a logarithmic barrier function to the objective function is added. Spinning reserve constraints are incorporated in the DED problem in [11] while the transmission line losses are considered in [36]. Han and Gooi [5] used the linear IP method and look-ahead decoupling method to solve the DED problem. Dual affine scaling algorithm is applied. Transmission line losses, spinning reserve and security constraints are all incorporated.

In [51,22] the security-constrained DED problem was solved by a modified version of the Han-Powell algorithm given in [81] which involves in a "compact reduced model" formulation. Further, a sparseness technique is used in the construction and updating the Hessian matrix of the Lagrangian function. In [22] both operating cost and ramp rate cost are included in the objective function. Granelli et al. [23], considered the DED problem formulated by [22] and presented a fast and efficient gradient projection algorithm for solving the problem.

Somuah and Khunaizi [4] proposed a redispatch technique for solving the DED problem with security and spinning reserve constraints as well as transmission line losses. In this technique, the ramp rate constraints are relaxed and the resulting SED problem is solved by quadratic programming. Then both the cost function and the constraints are linearized about the optimum points obtained from the SED problem and a new optimization problem (in terms of the output change) arises at each time interval. These optimization problems are combined in a single optimization problem after incorporating the ramp rate constraints which is solved by linear programming.

Barcelo and Rastgoufard [25] proposed an algorithm for solving the DED problem with network security and regulated margin constraints. The proposed algorithm is formulated by adding regulating margin and ramp rate constraints to the extended security constrained economic dispatch algorithm given in [82].

3.2. DED with artificial intelligence techniques

In the mathematical programming-based methods, the cost function is assumed to be smooth and convex. Hence these conventional methods are not suitable for determining the global optimal solution of the DED problem with valve-point effects or prohibited operating zones. In order to make the numerical methods more convenient in solving the DED problem with nonconvex, nonsmooth and nonmonotonically increasing incremental cost functions, artificial intelligence techniques such as artificial neural networks, stochastic optimization methods and hybrid methods that have been used to solve the DED problem. This is due to its ability to find a global or near global optimal solution.

Over the last decades, AI optimization algorithms have been applied to solve both SED and DED problems under various constraints. The question of how the constraints can be handled by these algorithms has been studied by several researchers (see the review in [83]). There are several methods of handling constraints, such as methods that preserve the feasibility, penalty-based methods, methods that clearly distinguish between feasible and infeasible solutions and hybrid methods [83]. The penalty-based methods are commonly used in solving the DED problem by AI techniques.

3.2.1. Neural network techniques

Artificial neural network (ANN) is an emulation of biological neural system and the brain. A neural network consists of many neurons connected in a parallel manner. ANN can be classified into several types according to the data type of inputs and training procedures. Hopfield neural network (HNN) is one of the ANN which is a single layer recursive neural network where all neurons are both input and output and they are connected with equal weights [84]. The energy function of the HNN model is defined in such a way that its time derivative is negative [40]. Therefore, the solution of the HNN is obtained when the energy converges to its minimum. In applying the HNN to the DED problem, the minimization of the cost function is equivalent to the search for a minimum energy function in the HNN model, and the decision variables in the optimization problem are represented by the output of the neurons. Then the task is to constitute a suitable energy function having the basic form of the energy function of HNN. Fukuyama and Ueki [28] applied neural network techniques in an attempt to solve the DED problem with security constraints. To suppress the local convergence, a probabilistic noise was added to the HNN model. The method was implemented using parallel processors. Liang [40] employed a redispatch technique for solving the spinning reserve constrained DED problem. Similar to the technique used in [4], the ramp rate constraints are relaxed and the SED problem is solved by the lambda-iterative method to produce the base solution. Then the problem with ramp rate constraints is linearized in accordance with this base solution and it is solved by gradient-type HNN. The main advantages of the HNN is its ability of parallel computing and obtaining good quality solutions [40]. The main drawback of the HNN is that, it converges slowly and normally takes a large numbers of iterations; the unsuitable sigmoid function may increase the computational time [70]. HNN has been used to solve the DED problem only with smooth cost functions.

3.2.2. Simulated annealing algorithm

The idea of the SA algorithm is devised from the annealing process of metals. Annealing refers to the process of heating up a metal to a high temperature followed by slow cooling achieved by decreasing the temperature in steps. At each step, the temperature is fixed for a period of time until the system reaches thermal equilibrium. Finally the system reaches its minimum energy crystalline structure [85]. SA technique is a random search technique for optimization developed by Kirkpatrick et al. [86] which simulates the physical annealing process. In SA the objective function corresponds to the energy of the metal and the number of iterations is equivalent to the temperature level in the annealing process. The temperature plays the role of control parameter for the optimization problem. The SA strategy starts with a high temperature and initial feasible solution which is assigned as the current solution. SA consists of a number of iterations, and each iteration contains a number of trials. In each trial a new feasible solution is generated by adding random perturbation to the current solution. The new solution is accepted if the objective function of the new solution is less than that of the current solution. Otherwise the new solution will be accepted with a certain probability. The accepted solution will be used to generate another solution. The procedure of generating a new solution and testing its acceptance is repeated for a specific number of trials. The last accepted solution will be used as the current solution of the next iteration. In the next iteration the temperature level will be reduced. The solution procedure continues until the maximum allowable number of iterations has been reached or there is no significant improvement in the solution after a pre-specified number of iterations [41].

SA has the ability to avoid getting local solutions; then it can generate global or near global optimal solutions for optimization problems without any restriction on the shape of the objective functions [41]. SA is not memory intensive [85]. However, the setting of control parameters of the SA algorithm is a difficult task and the computation time is high [15]. The computational burden can be reduced by means of parallel processing [41]. Panigrahi et al. [41] presented an SA technique for solving the spinning reserve constrained DED problem of units with valve-point effects and transmission line losses.

3.2.3. Genetic algorithm

Genetic algorithm (GA) is a search technique which is conceptually based on the mechanism of natural genetics and evolution [87]. GA uses genetic-like operators for searching the global optimum. GA starts with a population of candidate solutions chosen randomly within the feasible range, encoded in a binary string that forms chromosomes. Each member of the population is then decoded to pass through an evaluation process. The evaluation is based on a fitness function that basically depends on the objective function of the optimization problem. The initial population undergoes three main genetic operations, selection, crossover and mutation. Selection is an operation to choose parent solutions. Crossover operation is applied with a certain probability which combines two parent chromosomes to form two new offspring chromosomes having characteristics from both parents. After a new population has been generated by selection and crossover operations, a mutation is applied with small probability. Mutation is used to introduce new information to the population which does not exist in the parents. This process continues until the convergence criterion is met.

GA is a global and parallel search technique that can handle optimization problems with nonsmooth/nonconvex objective functions. Li et al. [33] employed GA to solve the DED problem with transmission line losses. The capability of GA in handling the constraints is explained. It is demonstrated that the ramping rate constraint does not put any additional burden on the genetic search but also helps in finding a better strategy to operate power systems. Ongsakul and Tippayachai [35] proposed a parallel micro genetic algorithm based on merit order loading solutions to solve DED problems for combined cycle units with linear decreasing and decreasing staircase incremental cost functions. The transmission line losses were taken into consideration. The proposed algorithm was implemented on eight processors. The main drawbacks of GA are the long computation time and the premature convergence.

3.2.4. Evolutionary programming

Evolutionary programming (EP) is a stochastic search technique which places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in GA [88,89]. EP starts with a population of randomly generated candidate solutions (parents) and finds solution in parallel using an evaluation process. At the start of the evolution process an initial population of target vectors (parents) is uniformly and randomly generated within the feasible range. A new population of solutions (offsprings) is created by mutation in such a way that an offspring is created from each parent by adding Gaussian random variable. The best individuals from parents and their offsprings having best fitness values are selected as new parents for the next generation. Mutation, competition and selection operations are repeated until the preset criterion is reached. EP has a global and parallel search capability and it can handle optimization problems with nonsmooth or nonconvex objective functions [89]. Compared with GA, EP does not use the crossover operator and the encoding and decoding schemes as does GA. Therefore, EP is faster in speed than GA [15]. Also EP can obtain better quality solution than GA [26]. However, EP requires long computation time and sometimes suffers from the convergence problem [15]. EP has been used to solve the DED problem with smooth [52] and nonsmooth cost functions [42].

3.2.5. Differential evolution

Differential evolution (DE) was introduced by Storn and Price [90] as a population-based stochastic parallel search technique. DE uses a rather greedy and less stochastic approach to problem solving compared to other evolutionary algorithms. It starts with an initial population of feasible target vectors (parents) and new solutions (offsprings) are generated (by mutation, crossover and selection operations) until the optimal solution is reached. In the mutation operation, three different vectors are selected randomly from the population and a mutant vector is created by perturbing one vector with the difference of the two other vectors. In the crossover operation, a new trial vector (offspring) is created by replacing certain parameters of the target vector by the corresponding parameters of the mutant vector on the bases of a probability distribution. In DE the competition between the parents and offspring is one to one. The individual with best fitness will remain till the next generation. The iterative process continues until a user-specific stoping criterion is met. DE has the ability to handle optimization problems with nonsmooth/nonconvex objective functions [90]. Moreover, it has a simple structure and a good convergence property, and it requires a few robust control parameters [90]. However, DE takes long computation time to get optimal solution.

Balamurugan and Subramanian [44] introduced DE algorithm and a look-ahead technique to solve the DED problem with valve-point effects. The same authors [43] developed an improved DE method to solve the same problem in [44]. The convergence of the DE algorithm is improved by introducing a heuristic crossover technique and a gene swap operator. Yuan et al. [53] used DE algorithm to solve the DED problem with valve-point effects. The constraints were handled by feasibility-based selection comparison techniques and heuristic search rules.

3.2.6. Particle swarm optimization

Particle swarm optimization (PSO) is a population-based stochastic search optimization technique first developed by Kennedy and Eberhart [91]. PSO is inspired by social behavior of bird flocking or fish schooling. PSO algorithm searches in parallel using a swarm consisting of a number of particles to explore optimal solutions. Each particle's position represents a candidate solution to the optimization problem. Each particle is initialized with a random position and random velocity within the feasible range. A fitness evaluation function is used to assign the fitness value of each particle. The best position among all particles is assigned and the best position of each particle up to the current iteration is also assigned. At each iteration, each particle updates its position based on its own best position and best swarm overall position assigned at the previous iteration and its previous velocity [92,93]. The procedure is repeated until the convergence criterion is satisfied.

PSO can be applied to global optimization problems with nonconvex or nonsmooth objective functions. PSO is easy in its concept and implementation and it has a few parameters to adjust [93].

Moreover, PSO can solve problems with high-quality solutions within shorter calculation time and stable convergence characteristics than other stochastic methods [70]. However, PSO, like all stochastic optimization techniques requires relatively a longer computation time than mathematical programming-based techniques [94].

Gaing [26] proposed a PSO method for solving DED problem with transmission line losses, spinning reserve and security, as well as prohibited operating zone constraints. In [45,39] a PSO technique is proposed to solve the DED problem with valve-point effects and transmission line losses. In the later paper [39] spinning reserve constraints were added to the problem. In [54] the DED problem with valve-point effects and transmission line losses was solved by PSO. The inequality constraints were handled by feasibility-based selection comparison techniques and the equality constraints were handled by heuristic strategies based on a priority list. Sriyanyong [55,56] presented an enhanced PSO for solving the DED problem with valve-point effects. The enhanced PSO consists of the standard PSO and a modified heuristic search approach which has the ability of handling the constraints. In [56] the enhanced PSO was combined with Gaussian mutation.

3.2.7. Hybrid techniques

Although the AI methods seem to be effective in solving the DED problem the obtained solutions are just near global optimum with long computation time [15,74]. Hybrid methods integrate two or more optimization techniques in order to combine their strengths and overcome one another's weakness in solving the optimization problems. These hybrid methods are found to be effective in finding global optimal solution for the DED with smooth/nonsmooth or convex/nonconvex cost functions. These hybrid methods include GA-SA [34], EP-SQP [15], PSO-SQP [30], EP-PSO-SQP [27], HNN-QP [46], etc. In these methods, initially one or more methods are used for the search purpose to find near optimal solutions; then the other method is used to fine-tune that region to get the final solution.

Abdelaziz et al. [46] introduced a hybrid approach of Hopfield neural network and quadratic programming (HNN-QP) to solve the DED problem with transmission line losses. The hybrid algorithm is based on using the HNN as a base search procedure to find a near optimal for the problem without ramp rate constraints. Then the problem with ramp rate constraints is solved by QP.

Ongsakul and Ruangpayoongsak [34] proposed a combined genetic and simulated annealing (GA-SA) algorithm to solve the DED problem for generating units with non-monotonically and monotonically increasing incremental cost functions. The transmission line losses were incorporated. SA is used to provide a base solution to the GA in order to reduce the search effort towards the optimal solution. It was shown that the proposed algorithm gives better solutions than GA and SA alone.

In [12,29] hybrid genetic algorithms are proposed to solve the DED problem with transmission line losses. The proposed hybrid scheme is developed in such a way that a genetic algorithm acts as a base level search and a local search method (gradient-search technique) is next employed to do the fine-tuning.

In [34,12,29,46] the nonsmooth or nonconvex characteristics of the cost function due to the valve-point effects or prohibited operating zones are neglected. Attaviriyanupap et al. [15] proposed a hybrid EP-SQP for solving the DED problem of units with valve-point effects. The hybrid method EP-SQP incorporates the EP algorithm as the main optimizer and the SQP as the local optimizer to fine-tune the EP search in finding the optimal solution. A 10-unit system was used to illustrate the effectiveness of the proposed method and comparisons are made with those obtained from EP and SQP alone.

Victoire and Jeyakumar [30] presented a hybrid approach by integrating the PSO with the SQP for solving the DED problem of units with valve-point effects. Transmission line losses were incorporated. In the proposed algorithm PSO is used as the base level search procedure and SQP is used to fine-tune for improvement in the solution obtained by using the PSO technique. The same authors in [31] added new constraints to the problem formulation given in [30] by introducing system spinning reserve and security constraints and the problem was also solved by hybrid PSO-SQP technique. In [32] a modified hybrid EP-SQP was presented for solving the same problem given in [30]. The proposed algorithm is implemented in such a way that the candidates of EP will explore the solution space freely, and then the SQP will be invoked when there is an improvement of solution in the EP run. The effectiveness of the proposed methods presented in [30–32] is demonstrated on a 10-unit system and compared with other methods.

Yuan el al. [57] proposed a hybrid improved differential evolution (IDE) with the Shor's r-algorithm for solving the DED problem of units with valve-point effects. The IDE is applied as a base level search which provides a near global solution region, and a local search Shor's r- algorithm is used as a fine-tuning to determine the optimal solution at the final.

Zhang et al. [58] proposed a hybrid genetic algorithm with quasi-simplex technique to solve DED problem with uncertainties in the coefficients of the cost function. The uncertainties were represented by fuzzy numbers. Zhang et al. [59] proposed a hybrid real-coded genetic algorithm with quasi-simplex technique to solve DED with valve-point effects. In [58,59] the proposed algorithms generate offsprings by using genetic algorithm and quasi-simplex technique in parallel.

Titus and Jeyakumar [27] presented a hybrid technique by integrating EP and PSO with SQP to the DED problem. Valve-point effects, transmission line losses and prohibited operating zones were all incorporated. Both EP and PSO are used as main optimizer to find a near global solution, while SQP is used for fine-tuning.

3.3. DED under emission limitations

The emission of gaseous pollutants including SO_2, NO_x, CO and CO_2 from fossil-fueled thermal generator plants affects human health directly or indirectly. Therefore, the controlling of pollution in power plants has received considerable attention in recent years. Emission can be reduced by various strategies such as installation of pollutant cleaning; switching to low emission fuels; replacement of the aged fuel burners with cleaner ones; emission dispatch [95]. The emission/economic dispatch approach is usually preferred to the existing systems because it is easy to implement and requires less additional cost.

The characteristics of emissions of various pollutants are different and usually highly nonlinear, which add more complexities to the economic dispatch problem. A summary of emission/economic dispatch algorithms is given in [95]. There are two main research directions to consider the emission in the DED problem. The first direction is to minimize the fuel cost while treating the emission as constraints. In this case, the amount of emission (E) of pollutants such as SO_x and NO_2 can be controlled by adding the following constraints to the original DED problem [95,96]:

$$E = \sum_{t=1}^{N}\sum_{i=1}^{n}[\alpha_i + \beta_i P_i^t + \gamma_i (P_i^t)^2 + \eta_i \exp(\delta_i P_i^t)] \le E^{\max} \tag{26}$$

where $E^{\max}$ is the maximum allowable amount of pollutant during the dispatch period, and α_i, β_i, γ_i, η_i and δ_i are the coefficient of the ith generator emission characteristics.

The second direction is to take the emission simultaneously as another objective to be minimized in addition to the fuel cost, i.e.

$$\mathrm{Min}[C, E]$$

subject to system and operational constraints.

In the literature an overwhelming number of reported works incorporate the emission with the SED problem (see e.g. [96–99] and the review paper [95]) but only few works address the DED problem with emission [16–18,60]. Wang et al. [100] and Granelli et al. [101] considered the emission in the dynamic dispatch problem as a constraint but they did not consider the ramp rate constraints in the problem. Song and Yu [21] added the emission and security constraints to the DED problem and used linear programming to solve the problem.

Recently the dynamic emission economic dispatch (DEED) problem has been formulated as a multi-objective optimization problem where the emission and economic dispatch are treated as competing and noncommensurable objectives [16–18]. In these papers the fuel cost function is incorporated with valve-point effects. In [16], by assuming that the decision maker has goals for each of the two objective functions, the multi-objective optimization problem is transformed into a single-objective optimization by the goal-attainment method that can be solved by PSO method. In [17] it was assumed that the decision maker has a fuzzy goal for each of the objective functions. The optimal noninferior generation schedule was determined by the EP-based fuzzy satisfying method. The results obtained from the proposed method were compared to those obtained by the fuzzy satisfying method based on the SA technique. In [18] the multi-objective problem is solved by nondominated sorting genetic algorithm-II. Shang et al. proposed a preference-based nondominated sorting genetic algorithm for solving the DEED problem [60].

4. DED in deregulated electricity markets

Recently many countries have gone through deregulation and restructuring the electrical power systems with the aim of improving economic efficiency. Deregulation means consumers will have their choice of electricity generation suppliers. After deregulation, the vertically integrated utilities were unbundled into generation companies (GENCOs), transmission companies (TRANSCOs) and distribution companies (TRANSCOs) [19]. A competitive electricity market has been created as a result of deregulation. In this environment, suppliers and sometimes customers can participate in the energy market as well as the reserve market. The independent system operator (ISO) is created to coordinate, control and monitor the operations of the electrical power systems. Market structures differ according to their participants and the amount of information that participants share with the ISO [102,103]. Under deregulated markets, all the transactions are made based on the price rather than cost. Of course, the DED formulation after deregulation is different from that before deregulation in some points as we will show in this section. The formulation of the DED problem will depend on the market structures.

In some markets the DED problem is the responsibility of the GENCO for scheduling and operating its power plants. In this case the GENCO runs the DED problem not for minimizing the production cost as in the regulated system but for maximizing its own profit. Here the profit is defined as the revenue minus generation cost. We shall refer to this problem as price-based dynamic economic dispatch (PBDED). The PBDED strategy can be used to build a successful bidding curve for the GENCO [19] wishing to maximize its profit. In recent years, some research has been done in building optimal bidding strategies for competitive suppliers. The bidding strategies problem was first introduced by David [104] and has been subseuently developed by many researchers (see e.g. [105–108] and the references therein). In a day-ahead energy market, suppliers submit monotonically inceasing bid curves (a pair of quantity and price) to the ISO. The ISO aggrerates the bid curves into an aggregated supply curve for each hour to determine the market clearing price (MCP) for that hour on the basis of the forecast load while maintaining system security and reliability.

In some other markets, large customers are premitted to bid in the market. Both supply-side and demand-side submit a daily bid curve including constraints for each generator and customer. The ISO utilizes DED problem to match bids so that the social profit is maximized and the security and reliability are preserved. The social profit is defined as the customer benefit minus generation cost [20]. This problem is referred to as bid-based dynamic economic dispatch (BBDED).

4.1. Price-based DED

The objective of PBDED is to maximize the GENCO's own profit regardless of the social profit. In this problem the GENCO runs its own PBDED based on the forecast energy and reserve demands and prices, and the probability that reserves are called into the actual operation. The solution of PBDED also depends on the way reserve payments are made. In general there are two types of reserve payment, payment for power delivered and payment for reserve allocated [109,19]. In the first payment method, reserve power is paid when only reserve is actually used. In the second payment method GENCO receives the reserve price per unit of reserve power even for the time period when the reserve is allocated and not used. If the reserve is used, GENCO can receive the energy price for the reserve that is generated. The objective function of the PBDED for the first payment method has been expressed as [19]:

$$\max PF = \underbrace{\sum_{t=1}^{N}\sum_{i=1}^{n} SP^t \cdot P_i^t + r \cdot RP^t \cdot S_i^t}_{\text{revenue}} - \underbrace{\sum_{t=1}^{N}\sum_{i=1}^{n}(1-r)\cdot C_i(P_i^t) + r \cdot C_i(P_i^t + S_i^t)}_{\text{cost}}$$

where SP^t and RP^t are the forecast energy and reserve prices, respectively, r is the forecast probability that the reserve is actually called up. Under the deregulation environment, the GENCO is not responsible for supplying the system energy and reserve demands which are the ISO's responsibility. Therefore, GENCO has the choice to sell energy and reserve at less than the forecast level, with its ultimate aim to maximize its own profit [19]. In this situation, the constraints (2) and (4) of the DED problem will be replaced by

$$\sum_{i=1}^{n} P_i^t \le D^t, \quad t = 1, 2, \ldots, N \tag{27}$$

$$\sum_{i=1}^{n} S_i^t \le SR^t, \quad t = 1, 2, \ldots, N \tag{28}$$

while other constraints may remain the same as in DED problem.

We note that the solution of the PBDED problem is more difficult than the convectional DED problem because in PBDED both the power and reserve are decision variables of the optimization problem [19]. Attaviriyanupap et al. [19] proposed a fuzzy-optimization approach to solve PBDED under uncertain power systems. The uncertainty parameters are represented by fuzzy numbers and consist of the energy demands, reserve demands, market prices and probability that reserves are actually called upon. The proposed algorithm determines the optimal amounts of power and reserve to be sold into the energy and spinning reserve markets. Yamin et al. [61] proposed an approach based on the Benders decomposition and the predictor-corrector primal-dual IP to solve the security constrained PBDED. In [61] spinning reserve requirements were not considered. Lee et al. [62] proposed a price-based ramp rate model for the application to the price-based dynamic dispatch. In this model the impact of binding ramp rate limits is reflected by hourly marginal ramp rate values of the generators and these marginal prices can be achieved by a simple iteration algorithm.

Now we can make a comparison between PBDED and DED:

1. The DED objective is to minimize the generation cost while PBDED objective is to maximize the GENCO's profit on the basis of the forecast energy and reserve prices [19,103].
2. In DED demand forecast advises the power system operator of the amount of power to be generated. But in PBDED, bilateral and forward contracts will make a part of the total demand and the remaining part will be forecast [110,103] as in DED.
3. In DED the total generation must equal the total demand; also, the total spinning reserve must be greater than assigned reserve requirements. In contrast the GENCO has the option to consider a PBDED schedule that produces less than the predicted power and reserve demands, with its aim to maximize its own profit [19].

4.2. Bid-based DED

In some deregulated markets, both suppliers and customers submit their bids along with their corresponding constraints in the hour-ahead and day-ahead to the ISO. The ISO obtains information from transmission companies on the transmission line capability and availability. Generally, the suppliers' and customers' bids are increasing and decreasing functions of the price, respectively. The ISO uses these bids submitted by supply-side and demand-side to determine the MCP and the corresponding supply and demand schedules of all generators and customers while maintaining system security. In this case the ISO runs a BBDED problem where the objective is to maximize the social profit with satisfaction of all constraints over the trading period. The problem of BBDED can be modeled as follows [20]:

$$\max PF = \sum_{t=1}^{N} \left\{ \sum_{j=1}^{n_d} B_j(D_j^t) - \sum_{i=1}^{n_g} C_i(P_i^t) \right\} \tag{29}$$

subject to

$$\begin{aligned}
&\sum_{i=1}^{n_g} P_i^t = \sum_{j=1}^{n_d} D_j^t + \text{Loss}^t, \qquad t = 1, 2, \ldots, N \\
&-DR_i \cdot T \le P_i^{t+1} - P_i^t \le UR_i \cdot T, \quad t=1, 2, \ldots, N-1, \quad i=1, 2, \ldots, n_g \\
&\underline{P}_i^t \le P_i^t \le \bar{P}_i^t, \qquad t = 1, 2, \ldots, N, \quad i = 1, 2, \ldots, n_g \\
&\underline{D}_j^t \le D_j^t \le \bar{D}_j^t, \qquad t = 1, 2, \ldots, N, \quad j = 1, 2, \ldots, n_d
\end{aligned} \tag{30}$$

where n_d and n_g are the number of customers, generators ; B_j and C_i are the bid functions of customer j and generator i, respectively; $\underline{D}_j^t$ and $\bar{D}_j^t$ are the minimum and maximum bid quantities of customer j at time t, respectively; $\underline{P}_i^t$ and $\bar{P}_i^t$ are the minimum and maximum bid quantities of generator i at time t, respectively. Other constraints have been considered in BBDED problem such as security and emission constraints [20,63].

Lin and Chen [20] proposed a predicted-corrected interior point quadratic programming algorithm to solve the BPDED problem. Zhao et al. [63] solved the same problem proposed by [20] by using PSO algorithm. In [63,20] the bid functions for customers and generators are assumed to be concave and convex, respectively.

In some electricity markets, only suppliers are allowed to submit bids to the ISO. In this case the ISO runs the BBDED to supply the load demand with maximum system-wide benefit, calculates the MCP and maintains system security. Ferreo and Shahidehpour [64] analyzed the effect of dynamic constraints on power transactions in a deregulated environment. They calculated the transition states using successive dynamic programming and employed Newton method to calculate optimal states within a utility for a given set of transactions.

4.3. DED with transmission cost (wheeling)

Wheeling has been defined as the use of utility's transmission facilities to transmit power over transmission lines. In deregulated markets, the owner's transmission system can be considered as the third party to provide wheeling for costumers and suppliers. Some countries adopt the policy of Transmission Open Access, which requires that each owner of transmission system allows the market participants to use his transmission system to transport power without discrimination [111]. The wheeling costs should be shared with participants who use the transmission facilities. Therefore, the economic dispatch problem must be modified to minimize not only the generation cost but also the wheeling cost. The wheeling cost has been taken into account in the economic dispatch problem in some papers (see e.g. [111,112]). However, the DED problem with wheeling cost has received less attention. Hosseini and Kheradmandi [65] considered the wheeling cost in the DED problem. Security constraints and transmission line losses were incorporated. The problem was solved by using GA.

5. Conclusion

This paper presents important features and considerations of the ODD problem. We first outlined two different formulations for the ODD problem and then presented a review of the optimization methods and techniques available for solving the problem. These methods are classified into mathematical programming-based methods, Artificial Intelligence (AI) techniques and hybrid methods. The mathematical programming-based or heuristically-based, such as the lambda iterative method, gradient projection method, Lagrange relaxation, linear programming, nonlinear programming, interior point methods and dynamic programming, etc. have proven their effectiveness in solving the DED problem with smooth, convex and strictly increasing incremental cost functions. For nonsmooth or nonconvex cost functions, most of these methods fail to obtain a global optimal solution. Recently, AI techniques such as GA, DE, EP, SA, and PSO have successfully been applied for solving DED with nonsmooth or nonconvex cost function due to their ability to seek the global optimal solution. However, it may take much time to reach just near a global optimum. Hybrid methods which combine two or more optimization techniques are found to be more effective in finding global optimal solution for the DED with nonsmooth or nonconvex cost functions.

This paper also presents an overview of the DED problem taking into account the emission of gaseous pollutants from thermal units. The emission has been considered either as an additional constraint to the DED problem or considered as another objective, where both emission and cost are minimized simultaneously.

The DED problem in deregulated power markets has been reviewed. Two forms of the problem have been presented. The first is refereed as price-based DED with the objective of maximizing the GENCO own's profit (revenue minus generation cost). The other problem is the bid-based DED with the aim of maximizing the social profit (customer benefit minus generation cost). The DED problem with transmission cost is also reported.

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