

# Review on Solution Techniques for Solving Power System Dynamic Economic Dispatch Problem

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**Abstract**— Dynamic Economic Dispatch (DED) is an important task in power generation planning in which the main aim is to decide the economic schedule of thermal generators over the scheduling time horizon. The output power of each generating unit is determined with respect to the predicted load demand over a planning period satisfying unit and system constraints. In practical systems, with change in load conditions, the power generation has to be altered to meet the demand. In this paper, the study is performed to review the various approaches that have been utilized to solve this complex DED problem. These approaches are broadly classified into three types, namely classical, heuristics and hybrid approaches. Based on the review, the analysis of various approaches is presented.

**Keywords**—Dynamic economic dispatch, artificial neural network, genetic algorithm, particle swarm optimization.

## I. INTRODUCTION

Due to the economic development, the energy demand has been increased during the recent years all around the world. This requires the electric generation utility to operate their generators at optimal condition. In this regard, the Economic Dispatch (ED) problem plays a vital role. ED confirms the economic schedule of the generators as per the load demand [1]. However, the load demand is not fixed and follows different load cycles. Therefore, the generation could not be constant through the planning period. However, the power output of thermal generators could not be increased beyond their stress limits and follows ramp cycles of power generation. The inclusion of these ramp rates in the modeling of ED problem makes it dynamic and called Dynamic Economic Dispatch (DED) [2]. DED seeks the best generation schedule for the generating plants to supply the required demand and transmission losses with the minimum production cost [3].

The DED problem could be solved using various optimization techniques, which are broadly classified into three categories, namely classical, heuristics and hybrid approaches. A number of conventional approaches that have been applied for solving DED problem are multilevel technique [4],

dynamic programming (DP) [5], linear programming (LP) [6], weighted mini-max [7], quadratic programming (QP) [8], goal programming (GP) [9], lambda iteration method (LIM) [10], Lagrange relaxation algorithm (LRA) [11]. These classical algorithms require incremental cost curves that are monotonically increasing or piece-wise linear in nature. But normally the input-output characteristics of modern generating units are highly nonlinear in nature due to valve-point effects; ramp-rate limits etc. having multiple local minimum points in the cost function. Thus, the characteristics of DED problems are multiple, discontinuous and highly nonlinear. Due to such approximation, the solution is subnormal and hence, a huge amount of revenue loss occurs over the time. Dynamic Programming imposes no restrictions on the nature of the cost curves but this method suffers from the curse of dimensionality in the solution procedure. On the other hand, the various heuristic approaches that have been utilized to solve DED problem are genetic algorithm (GA) [12], efficient technique [13], particle swarm optimization (PSO) [14], simulated annealing (SA) [15], Tabu Search Algorithm (TSA) [16], bacterial foraging algorithm (BFA) [17], gravitational search algorithm (GSA) [18], teaching learning based algorithm (TLBA) [19], bee colony optimization (BCO) [20], backtracking search algorithm (BSA) [21], social spider algorithm (SSA) [22], gray wolf optimization (GWO) [23].

However, these single approaches classical and heuristics are not sufficient alone to provide the global optimal solutions, therefore researchers have proposed hybrid approaches to solve DED problem. Various hybrid approaches are hybrid of DE and Biogeography-based Optimization (BBO) [24], hybrid of chaotic PSO and sequential quadratic programming (SQP) [25], hybrid of DE and PSO [26], hybrid of GA-micro-genetic algorithm (MGA) [27], hybrid krill herd algorithm (HKHA) [28], hybrid of PSO-GSA [29] and hybrid of bee algorithm (BA) and tabu search (TS) [30].

## II. PROBLEM FORMULATION

The primary objective of DED problem is to reduce the operational cost of system fulfilling the load demand within limit of constraints. However due to growing concern of environment, there are

various kinds of objective function formulations and techniques as given in subsequent sections. The formulation of DED problem has expressed as given below:

$$F = \sum_{t=1}^T \sum_{i=1}^N F_{it}(P_{it}) \quad (1)$$

where,  $F$  is total operating cost of all generating units over all dispatch periods,  $T$  is number of hour in the time horizon,  $N$  is number of generating units and  $F_{it}(P_{it})$  is the fuel cost in term of its real power output  $P_{it}$  at a time  $t$  and  $P_{it}$  is the output power of  $i$ th unit at time  $t$ .

The fuel cost function with valve point effect of the thermal generating unit is expressed as the sum of a quadratics and sinusoidal functions.

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i + |e_i (\sin(f_i (P_{i\min} - P_{it})))| \quad (2)$$

where,  $a_i$ ,  $b_i$ ,  $c_i$ ,  $e_i$  and  $f_i$  are constraints of fuel cost function of  $i$ th unit.

#### A. Power Balance Constraint

$$\sum_i^N P_{it} - P_{Dt} - P_{lt} = 0 \quad ; t=1,2,\dots,T \quad (3)$$

where  $P_{Dt}$  is the total power demand at time  $t$ ,  $P_{lt}$  is the total transmission loss during  $t$ th dispatch period.

#### B. Power Operating Limits

$$P_{i\min} \leq P_{it} \leq P_{i\max} \quad ; i=1,2,\dots,N \text{ and } t=1,2,\dots,T \quad (4)$$

where,  $P_{i\min}$  and  $P_{i\max}$  are the minimum and maximum real power output of  $i$ th generator respectively.

#### C. Ramp Rate Limits

$$P_{it} - P_{i(t-1)} \leq UR_i \quad ; i=1,2,\dots,N \text{ and } t=1,2,\dots,T \quad (5)$$

$$P_{i(t-1)} - P_{it} \leq DR_i \quad ; i=1,2,\dots,N \text{ and } t=1,2,\dots,T \quad (6)$$

where,  $UR_i$  and  $DR_i$  are ramp up and ramp down rate limits of  $i$ th generator respectively and expressed in MW/h.

### III. SOLUTION TECHNIQUES

It is observed that a large number of techniques have been proposed in the literature to solve the DED problem. Out of which, the main techniques that are used frequently are presented as follows:

- A. Artificial Neural Networks
- B. Genetic Algorithm
- C. Particle Swarm Optimization

#### A. Artificial Neural Networks

Artificial Neural networks (ANNs) have self adapting capabilities which make them well suited

to handle non-linearity's, uncertainty and parameter variations which may occur in DED problems. Feed-forward back propagation neural network is an example of non-linear layered feed-forward networks [31]. Back propagation neural networks construct global approximations to non-linear input-output mapping. These ANNs have capability of generalization in regions of the input space where little or no training data are available. Artificial Neural Networks are inherently capable of giving optimal results but it has some drawbacks:

- Processing time can rise quickly as the size of the problem grows.
- The performance of a neural network is sensitive to the quality and quantity of training data. It is also affected by the type of preprocessing (normalization) of the input data.
- The numbers of hidden layers is problem dependent and as the complexity of problem increases more number of hidden layers are needed.

The output of ANN is dependent on how accurately it is trained and which training algorithm is used for training like simple gradient descent, adaptive (learning rate and momentum factor) gradient descent method, Liebenberg-Marquardt (LM) learning etc.

#### B. Genetic Algorithm

To overcome above disadvantages, a new optimization technique called Genetic Algorithm (GA) is used. Genetic algorithm (GA) is essentially a search algorithm based on the mechanism of nature (e.g. natural selection, survival of the fittest) and natural genetics. They combine solution evaluation with randomized, structured exchanges of information between solutions to obtain optimality [12]. Evolutionary programming (EP) is a stochastic optimization strategy similar to genetic algorithm. Evolutionary programming is a computational intelligence method in which an optimization algorithm is the main engine for the process of three steps, namely, natural selection, mutation and competition. It is a stochastic optimization strategy, which places emphasis on the behavioral linkage between parents and their off-spring, rather than seeking to emulate specific genetic operators as in GA's. Evolutionary programming tends to generate more effective and efficient searches. It operates on populations of real values (floating points) that represent the parameter set of the problem being solved over some finite ranges. Evolutionary programming is a near global stochastic optimization method which places emphasis on the behavioral linkage between parents and their off-spring, rather than seeking to emulate specific genetic operators as observed in nature to find a solution.

The global optimization techniques (known as genetic algorithm is the forms of probabilistic heuristic algorithm) have been successfully used to

overcome the non convexity problems of the constrained Economic Dispatch. Genetic Algorithm has slow convergence near global optimum, sometimes may be trapped into local optimum which lead to new swarm based optimization technique, called particle swarm optimization.

### C. Particle Swarm Optimization

Particle swarm optimization was first introduced by Kennedy and Eberhart in the year 1995. It is an exciting new methodology in evolutionary computation and a population-based optimization tool like GA. PSO is motivated from the simulation of the behavior of social systems such as fish schooling and birds flocking. The PSO algorithm requires less memory because of its inherent simplicity [14]. PSO is similar to the other evolutionary algorithms in that the system is initialized with a population of random solutions, call particle (swarm), flies in the d-dimension problem space with a velocity, which is dynamically adjusted according to the flying experiences of its own and colleagues. Swarms collect information from each other through an array constructed by their positions using the velocity of particles. Position and velocity are both updated by using guidance from particles' own experience and experience of neighbors. The position and velocity vectors of the  $i$ th particle of a d-dimensional search space can be represented as  $X_i = (x_{i1}, x_{i2}, \dots, x_{id})$  and  $V_i = (v_{i1}, v_{i2}, \dots, v_{id})$ .

On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as  $p_{best} = (p_{i1}, p_{i2}, \dots, p_{id})$ . If the  $g^{th}$  particle is the best among all particles in the group so far, it is represented as  $p_{bestg} = gbest = (p_{g1}, p_{g2}, \dots, p_{gd})$ . The particle tries to modify its position using current velocity and the distance from pbest and gbest. The modified velocity and position of each particle for fitness evaluation in the next iteration, i.e., (k+1)th iteration, are calculated using following equations:

$$v_{id}^{k+1} = W * v_{id}^k + c_1 * rand1 * (pbest_{id} - x_{id}^k) + c_2 * rand2 * (gbest_{id} - x_{id}^k) \quad (7)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (8)$$

where,  $W$  is the inertia weight that controls the global and local exploration capabilities of the particle,  $c_1$  and  $c_2$  are cognitive and social coefficients, respectively, rand1 & rand2 are random numbers between 0 and 1.

$c_1$  pulls the particles towards local best position and  $c_2$  pulls towards the global best position. Usually these parameters are selected in the range of 0 to 4. In the procedure of the particle swarm paradigm, the value of maximum allowed particle velocity ( $v_{max}$ ) determines the resolution, or fitness, with which

regions are to be searched between the present position and the target position. If  $v_{max}$  is too high, particles may fly past good solutions. If  $v_{max}$  is too small, particles may not explore sufficiently beyond local solutions. Thus, the system parameter  $v_{max}$  has the beneficial effect of preventing explosion and scales the exploration of the particle search. Suitable selection of inertia weight  $W$  provides a balance between global and local explorations, thus requiring less iteration on an average to find a sufficiently optimal solution. The variation of  $W$  between the limits 0.9 to 0.4 is done as follows:

$$W = (w_{max} - w_{min}) * \frac{iter_{max} - iter}{iter_{max}} + w_{min} \quad (9)$$

where,  $w_{max}$  is the initial weight,  $w_{min}$  is the final weight,  $iter_{max}$  is the maximum iteration number, and  $iter$  is the current iteration number.

The equation (7) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and the group's best experience. Then the particle flies towards a new position according to equation (8). The performance of each particle is measured according to a predefined fitness function, which is related to the problem to be solved.

### IV. CONCLUSIONS

In this paper, the study work has been conducted on dynamic economic dispatch (DED) problem and different solution techniques to solve DED problem. It is observed from the literature survey that the solution techniques are basically classified into three different categories as classical, heuristics and hybrid. The classical techniques are found to be a better optimization technique for convex DED problem. However, when the function to be optimized becomes nonlinear or non-convex, the heuristic optimization techniques are claimed to achieve a better optimal solutions. Although the heuristic techniques are quite instrumental in searching out the best and optional solution to DED problem but their hybridization moves a step ahead in achieving near global optimal solutions in reasonable execution time. Therefore, it becomes imperative to have the synergism of intelligent techniques as per the requirements and also to cope up with the present trend.

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