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Stochastic Economic Load Dispatch with Multiple Fuels using Improved Particle Swarm Optimization

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Abstract: In this paper, Stochastic Economic Load Dispatch (ELD) problem with multiple fuels is solved using Improved Particle Swarm Optimization (IPSO). Generally, ELD problem is solved using deterministic models, but data required for such studies are rarely available with complete certainty. So uncertainties in unit's generation, load demand and cost coefficients should be considered to get actual scenario. Thus, stochastic model for ELD problems is more suitable than deterministic model from the utilities point of view. ELD problem with deterministic model is first solved using IPSO to examine the effectiveness of the proposed method. Then IPSO is applied for ELD problem with stochastic model to investigate the real generation cost.

Keywords: Economic Load Dispatch, Multiple Fuel Generation, Particle swarm optimization.

1. INTRODUCTION

Due to highly competitive electric market, depletion of fossil fuels and rapid escalation of fuel prices, the main goal of Generation Companies (GenCos) is to generate the given amount of power at the lowest possible cost, i.e., by least use of fossil fuels. Economic Load Dispatch (ELD) is an important optimization problem in power system operation to allocate the total power demand among the committed units economically, while satisfying various constraints (Wood and Wollenberg, 1996). In old days, the cost function of each generator was approximated monotonically increasing in nature either piece-wise linear or quadratic. Using such cost functions, traditional methods like lambda iteration, base point participation factor (Wood and Wollenberg, 1996), gradient method and Newton method (Zhu, 2009), could solve ELD problems very effectively. But, practically generators have non-differential cost curve due to prohibited operating zones, valve point effects, and multi-fuel options. With these constraints and effects, the modern ELD became a complex optimization problem and traditional methods cannot provide quality solutions (Amjady and Rad, 2009). However, the performance of Dynamic Programming (DP) (Liang and Glover, 1992) does not depend on nature of the cost curve, but it suffers from the curse of dimensionality.

As practical ELD problems are very difficult to solve mathematically, a large number of meta-heuristic methods like Genetic Algorithm (GA) (Chen and Chang, 1995), Evolutionary Programming (EP) (Jayabarathi and Sadasivam, 2000), Tabu Search (Lin et al., 2002), Adaptive Hopfield Neural Network (AHNN) (Lee et al., 1998), Particle Swarm Optimization (PSO) (Gaing, 2003), Bacterial Foraging (BF) (Panigrahi and Pandi, 2008), Ant Colony Optimization (Song and Chou, 1999), etc. have been successfully applied to solve them. Though these techniques do not guarantee to provide the global optimal solution, they can normally produce sub-optimal solutions in a reasonable computational time. These methods in their original form have the problem of trapping into the local optima. Therefore, lots of modifications are suggested to these methods to improve the quality of solution (Vlachogiannis and Lee, 2009; Park et al., 2010; Amjady and Rad, 2009). Meanwhile some researchers have reported the use of hybrid approaches to solve ELD more effectively (Niknam, 2010; Bhattacharya and Chattopadhyay, 2010).

However, in most of these studies, ELD is solved with deterministic models, which is not capable to represent the practical situation, due to the inaccuracy and uncertainties in forecasting and measurement. Therefore, it would be more preferable to construct the stochastic model, upon which load dispatch should be solved. A very few studies have been conducted to deal with the stochastic load dispatch problem.

Bunn and Paschentis, 1986 solved ELD problem, where mismatch between actual load demand and dispatched generation is considered. Dhillon et al., 1993 solved the multi-objective load dispatch problem by weighted minimax. Kasangaki et al., 1995 solved unit commitment and economic load dispatch considering uncertainties in load demand and unit availability by using stochastic Hopfield artificial neural networks. Selvi et al., 2004 solved the ELD incorporating uncertainties in cost data by GA. Wang and Singh, 2008 formulated and solved ELD problems under different uncertain conditions by using modified PSO. Trivedi et al., 2013 solved generation scheduling under uncertain environment.

In practice, many generating units are supplied with multi-fuel source, lead to the problem of determining the most economic fuel to burn (Lin and Viviani, 1984). In this paper, ELD problem with multiple fuels is solved considering its stochastic behaviour where load demand and fuel cost coefficients are treated as stochastic variables. An improved particle swarm optimization (IPSO) algorithm is initially used to solve the ELD problem with deterministic model.

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Comparative study is conducted to check the effectiveness of the proposed approach. Then, proposed IPSO is applied to solve the stochastic ELD problem. The results of deterministic and stochastic ELD are compared. Finally, the conclusion is drawn from the results obtained.

2. PROBLEM FORMULATION

The typical formulations of power generation scheduling problems are considered to be deterministic, as these are assumed disturbance free and accurate (Dhillon et al., 1993). But, this assumption is not appropriate for practical applications, as uncertainties is available everywhere due to inaccuracies in the process of measuring and forecasting of input data and changes of unit performance during the period between measuring and operation. So deterministic model don't reflect the real situations in power generation scheduling problem and these deviation must be considered by generation utilities (Kasangaki et al., 1995).

In this section, the stochastic model of objective in the ELD with multiple fuel and concerned constraints are presented. The load demand and fuel cost coefficients are normally distributed and inter-dependent and considered as random variables.

2.1 *Stochastic Model for ELD with Multiple Fuels*

In real power plants, there may be generating units supplied with multiple fuels. In these cases, each generating unit has a set of cost curves, corresponding to the type of fuel being burned. Therefore unit's cost function is composed of a set of smooth fuel cost functions $F_i(P_j)$ (Amjady and Rad, 2009).

The deterministic model of fuel cost is approximated by a set of quadratic function for each generator output P_i

$$F(P_{ij}) = \sum_{i=1}^{N}(a_{ij}{P_i}^2 + b_{ij}P_i + c_{ij}) \quad (1)$$

where, i shows generating units and j shows fuel type used, a_{ij}, b_{ij} and c_{ij} are the cost coefficients of i_{th} generator corresponding to j_{th} fuels.

The stochastic model of $F_i(P_{ij})$ can be derived using Taylor's series expansion around the mean. Then the expected fuel cost can be obtained through the expectation of the expanded form (Wang and Singh, 2008):

$$\bar{F}(P_{ij}) = \sum_{i=1}^{N}[\bar{a}_{ij}\,\bar{P}_i^2 + \bar{b}_{ij}\bar{P}_i + \bar{c}_{ij} + \bar{a}_{ij}var(\bar{P}_i) + 2\bar{P}_i cov(a_{ij},P_i) + cov(b_{ij},P_i)] \quad (2)$$

where $\bar{p_i}$ is the expected generation of i_{th} generator, and $\bar{a}_{ij}$, $\bar{b}_{ij}$,and $\bar{c}_{ij}$ are the expected fuel cost coefficients of i_{th} *generator for j_{th} fuel*. Then equation can be rewritten as:

$$\bar{F}(P_{ij}) = \sum_{i=1}^{N}[(1 + C_{P_i}^2 + 2R_{a_{ij}Pi}C_{a_{ij}}C_{P_{ij}})\,\bar{a}_{ij}P_i^2 + \left(1 + R_{b_{ij}Pi}C_{b_{ij}}C_{P_{ij}}\right)\bar{b}_{ij}\bar{P}_i + \bar{c}_{ij}] \quad (3)$$

where, C_{P_i}, $C_{a_{ij}}$, and $C_{b_{ij}}$ are the coefficients of variation of the random variables P_i, a_{ij} and b_{ij}, respectively. Coefficient of variation is defined as the ratio of standard deviation to the mean of the respective random variable. It measures the relative dispersion or uncertainty of the concerned random variable. The randomness of random variable is proportional to the coefficient of variation. $R_{a_{ij}Pi}$ is correlation coefficient of the variables a_{ij} and P_i. $R_{b_{ij}Pi}$ is correlation coefficient of the variables b_{ij} and P_{i}.

As transmission power loss is assumed to be zero, the real power generated must be equal to the demand throughout the system operations:

$$\sum_{i=1}^{N} P_i = \bar{P}_D \quad (4)$$

where, $\bar{P}_D$ is the expected power demand.

The expected power generation of each generator is restricted by its generator capacities:

$$\bar{P}_i^{min} \le \bar{P}_i \le \bar{P}_i^{max} \quad (5)$$

$\bar{P}_i^{min}$ and $\bar{P}_i^{max}$ are the expected lower and upper power limit of the i_{th} generator, respectively.

3. PROPOSED METHODOLOGY

It will be very important to review the basics of the standard PSO first in order to introduce the IPSO. Similar to the other evolutionary algorithms Particle swarm optimization is a population based optimization search technique. PSO was proposed by Kennedy and Eberhart, which is inspired by the social phenomenon of fish schooling and birds flocking (Kennedy and Eberhart, 1998).

In standard PSO, a swarm of feasible particle is randomly generated in the search space and velocity vector is initialized for each particle. Then, fitness value for each particle is calculated according to the objective function. Then particles basically utilize two important kinds of information sharing in decision process. The first one is their own experience; the second one is other particle's experiences. Then particle flies in the N-dimensional search space with its velocity, which is influence by the three components namely, inertial component, cognitive component and the social component (Kennedy and Eberhart, 1998). During evolution process each particle updates its velocity and position vector according to the following model:

$$w = w_{max} - \frac{w_{max}-w_{min}}{iter_{max}} \times iter \quad (6)$$

$$V_{ij}^t = wV_{ij}^{t-1} + C_1 rand_1()\left({P_{best}}_{ij}^{t-1} - P_{ij}^{t-1}\right) + C_1 rand_2()\left({G_{best}}_{j}^{t-1} - P_{ij}^{t-1}\right) \quad (7)$$

$$P_{ij}^t = P_{ij}^{t-1} + V_{ij}^t \quad (8)$$

w=inertial factor
w_{min}=Minimum value of inertial factor = 0.1
w_{max}= Maximum value of inertial factor = 1
C_1=cognitive acceleration co-efficient=2
C_2=social acceleration co-efficient=2
$rand_1$=random value between 0 and 1
$rand_2$= random value between 0 and 1

where, *i, j & t* represents particle, dimension of the problem and iteration respectively.

The previous best position of each particle is recorded as P_{best} and the previous best among the particles is represented by