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Stochastic Economic Load Dispatch Using Pareto Distribution With Multiple Fuels Local Convex By Bacterial Foraging Optimization

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Abstract: In this paper Stochastic Economic Load Dispatch problem with Multiple Fuels is solved using Pareto distribution with local convex optimization by bacterial foraging approach. Bacterial foraging optimization is swarm intelligence technique used to solve problem of power system. The algorithm is based on the group foraging behavior of Escherichia coli (E-coli) bacteria present in the human intestine. This social behavior of E-coli bacteria has been used to solve optimization problems. This paper presents a BFO to solve Economic load dispatch (ELD) problems. The result is obtaining from test system with seven generating units. In this paper performance of the BFO is compared with Particle swarm optimization (PSO). The result clearly shows that the proposed method gives a better optimal solution as compared to the other methods.)

Keywords: Economic Load Dispatch (ELD), Multiple Fuel Generation, Bacterial Foraging Optimization (BFO).

I. INTRODUCTION

In the power system planning and operation, the economic load dispatch (ELD) is meant the security of low-cost generating power as load demands according to the system constraints. This is one of the most critical issues that have been researched recently.

Economic load dispatch (ELD) is a very important problem to power system operation since this task decides the economy of the power system. In fact, the electricity generation fuel cost of a power system mainly using fossil fuel to produce electricity is very high compared to other sources. Furthermore, the fossil fuel is not plentiful and exhausted in the near future. Consequently, optimal operation of thermal plants has played a significantly important role so far. In the past, the fuel cost curve of the thermal unit is expressed as a single quadratic function because each considered unit used only one fuel and the valve-point loading effect was not taken into account. Nowadays, the cost curve is more complicated as considering multiple fuels and valve-point loading effect [1].

Several methods have been successfully applied to ELD problem with multiple fuel options so far including lambda-iteration [2], Hopfield neural network (HNN) [3], Enhanced Lagrangian neural network (ELANN) [1], augmented Lagrange Hopfield network (ALHN) method [4], approximately equivalent function based ALHN (AEALHN) [5].

Recent years, many meta-heuristic algorithms and Hopfield network-based methods have attracted many attentions from a researcher in applying to the economic load dispatch where multiple fuel options are considered. These methods include Particle swarm optimization (PSO) [6], Differential Evolution (DE) [7], Self-Adaptive Differential Evolution (SDE) [8], Genetic algorithm (GA) [9-10] and evolutionary programming (EP) [11]. PSO can produce high-quality solutions in short period time.

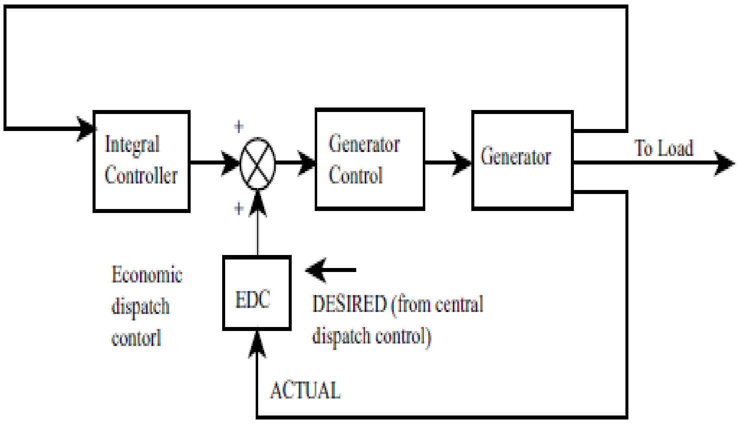


Figure 1.1 Valve point loading of the system

However, the method is sensitive to the selection of control parameters and it is not very efficient for nonconvex objective function. DE is a powerful search tool for a global optimal solution. Nevertheless, the DE method is still slow for applying to large-scale problems. Compared to DE, SDE is a good method to solve ELD problem with Valve-Point Effects. Among the methods, GA is the weakest one since it is vastly dependent on the fitness function and sensitive to the mutation and crossover operations and must spend long time searching solution. The manners lead to the limitation of the GA on the complex systems. EP has a high performance for optimization problems but it is as good as DE and PSO.

However, the disadvantages of the method are that the values of lambda and updated step size are randomly chosen initially. This can lead to a non-optimal solution or non-convergence. The best solution has been found after the method has been performed 93 independent runs with various values of lambda and fuel type. The computational time for each trial is short but total time for the whole is long. Enhanced Augmented Lagrange Hopfield Network (ALHN) [4] solves ELD problem in two phases and gains good solutions and short simulation time. However, the gained simulation results depend on setting a large number of parameters. The Differential Evolution (DE) [5] algorithm is found to be a powerful evolutionary algorithm for global optimization in many real problems. Self-Adaptive Differential Evolution (SDE) [6] is a good method to solve ELD problem with valve-point effects. The application of Hopfield neural network (HNN) [7] with the merit of simplicity created difficulties in handling some kinds of inequality constraints. For solving the problem by the enhanced Lagrangian neural network (ELANN) [1] method, the dynamics of Lagrange multipliers including equality and inequality constraints were improved to guarantee its convergence to the optimal solutions, and the momentum technique was also employed in its learning algorithm to achieve the fast computational time.

Particle Swarm Optimization [8] (PSO) is one of the modern heuristic algorithms and has a great potential to solve complex optimization problems. PSO algorithm is highly robust yet remarkably simple to implement. Thus, it is quite pertinent to apply the PSO with new modifications to achieve better optimization and handle the power system problems efficiently [9].

A hierarchical approach based on the numerical method (HNUM) [9] is one of conventional method which is non-effective for solving on smooth fuel cost function. With a parallel searching mechanism, the improved evolutionary programming (IEP) [11] method has a high probability of finding an optimal solution. By combining equivalent function and Lagrange multiplier theory or Hopfield Lagrange network, two methods including Lambda Iterative (LI) and Hopfield Lagrange network have been proposed for solving economic dispatch [12]. The two methods have obtained good solution quality; however, the applicability of the two ones is restricted on the system with valve point effect on thermal units. The genetic algorithm (GA) [13] is critically dependent on the fitness function and sensitive to the mutation and crossover rates, the encoding search space curve leading toward solutions.

The cuckoo search algorithm (CSA) developed by Yang and Deb in 2009 [14] is a new meta-heuristic algorithm for solving optimization problems inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds of other species. To verify the effectiveness of the CS algorithm, Yang and Deb compared its performance with particle swarm optimization (PSO) and GA for ten standard optimization benchmark functions.

This paper focuses on bacterial foraging optimization algorithm to solve the problem of economic load dispatch problem including valve-point effects.

MATHEMATICAL FORMULATION

The concept behind economic load dispatch problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system [8]. Therefore, it can be formulated mathematically with a goal function and equality and inequality constraints.

Objective function:

$$MinF_T = \sum_{i=1}^{N_G} F_i(P_{Gi}) = \sum_{i=1}^{N_G} \left(a_i P_{Gi}^{\ 2} + b_i P_{Gi} + c_i\right)$$

Where

F_T is the total generation cost (\$/hr)

F_i is the fuel-cost function of generator i (\$/hr) NG is the number of generators

P_{Gi} is the real power output of generator i (MW) and ai , bi and ci are the fuel-cost coefficients of generator

The basic constraints are the real power balance and the real power operating limits

$$\sum_{i=}^{N_G} P_{G_i} = P_{Load} + P_{Loss}$$

$$P_{G_i} \min \le P_{G_i} \le P_{G_i} \max \qquad i = 1,2,3......N$$

Where

P_{Load} is the total load in the system (MW)

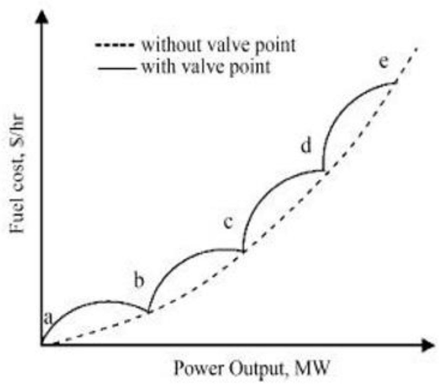
P_{Loss} is the network loss (MW) and

P_{Gi}^{min} & P_{Gi}^{max} are the minimum and maximum power generation limits of generator

Generally, large turbogenerators have a set of valves at the inlet to the steam turbine. With the increase in power demand, these valves are opened sequentially. The throttling loss in a valve is large when it is just opened and is small when it is fully opened. This is known as valve-point loading effect which makes the cost curve highly nonlinear and nonconvex as shown in Fig. 1. This phenomenon can be simulated using a recurring rectified sinusoidal function superimposed with the conventional quadratic cost function. The total cost of generation can be expressed as:

$$MinF_T = \sum_{i=1}^{N_G} \left(a_i P_{Gi}^{\ 2} + b_i P_{Gi} + c_i\right) + \left| e_t \sin f_t \left\{ P_{Gi}^{\min} - P_{Gi} \right\} \right|$$

Where e_i , f_i are constants from the valve point effect of the generating unit *i*. and *a, b, c* are the coefficients.



BACTERIAL FORAGING OPTIMIZATION

BFO method was invented by Kevin M. Passino [12] motivated by the natural selection which tends to eliminates the animals with poor foraging strategies and favor those having successful foraging strategies. The foraging strategy is governed basically by four processes namely Chemotaxis, Swarming, Reproduction, Elimination and Dispersal [14].

A. Chemotaxis

Chemotaxis process is the characteristics of movement of bacteria in search of food and consists of two processes namely swimming and tumbling. A bacterium is said to be 'swimming' if it moves in a predefined direction, and 'tumbling' if moving in an altogether different direction. Let j be the index of chemotactic step, k be the reproduction step and l be the elimination dispersal event. Let is the position of ith bacteria at jth chemotactic step, kth reproduction step, and lth elimination dispersal event. The position of the bacteria in the next chemotactic step after a tumble is given by If the health of the bacteria improves after the tumble, the bacteria will continue to swim in the same direction for the specified steps or until the health degrades.

B. Swarming

Bacteria exhibits swarm behavior i.e. healthy bacteria try to attract other bacteria so that together they reach the desired location (solution point) more rapidly. The effect of Swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density. Mathematically swarming behavior can be modeled as [4]:

C. Reproduction

In this step, population members who have had sufficient nutrients will reproduce and the least healthy bacteria will die. The healthier half of the population replaces with the other half of bacteria which gets eliminated, owing to their poorer foraging abilities. This makes the population of bacteria constant in the evolution process.

D. Elimination and Dispersal

In the evolution process, a sudden unforeseen event may drastically alter the evolution and may cause the elimination and/or dispersion to a new environment. Elimination and dispersal help in reducing the behavior of stagnation i.e. being trapped in a premature solution point or local optima.

II. RESULTS AND ANALYSIS

The simulation is carried out for seven generating units with considering the demand of the load. BFO is implemented for solving this problem at different power demand but demand is varying at different hours as shown in table [1.1].

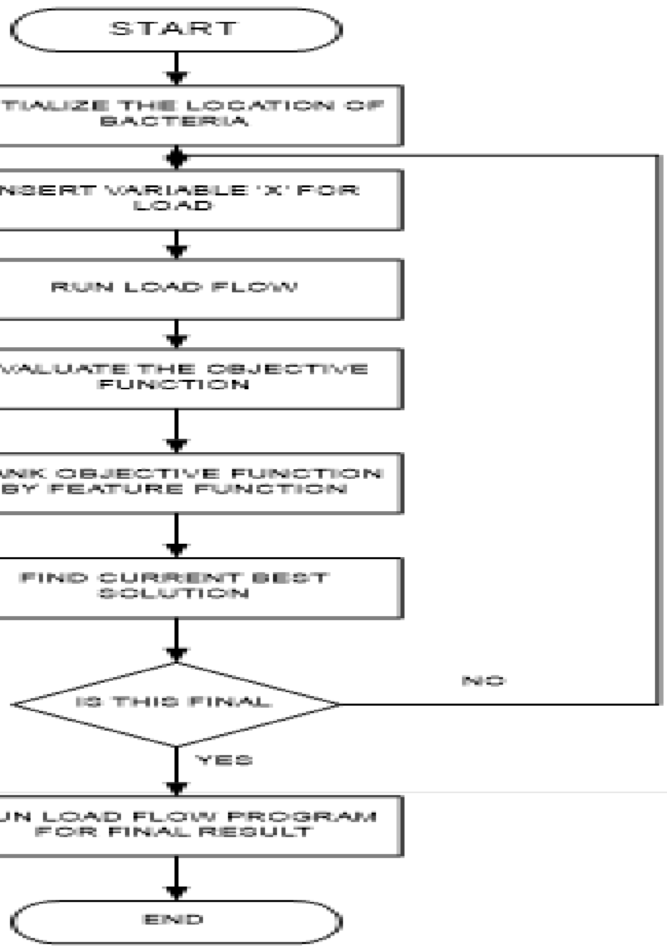


Table 1.1 Power (MW) of Generation units

Generation units	PSO Power (MW)	BFOA Power (MW)
1	239.5969	245.5969
2	278.5398	278.5398
3	239.558	239.558
4	288.7784	298.7784
5	239.6549	249.6549
6	428.3248	428.3248
7	274.8201	284.8201

Table. 1.2 Fuel Cost of Generation units

Generation units	PSO Cost	BAFO Cost
1	47.33106	34.33106
2	72.30011	71.30011
3	46.81139	40.81139
4	72.98287	65.98287
5	47.36043	44.36043
6	118.7445	100.7445
7	69.8813	66.8813

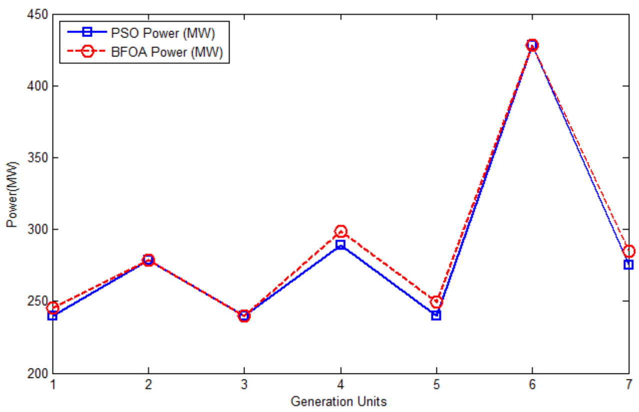


Fig. 1.2 Power with BFO and PSO

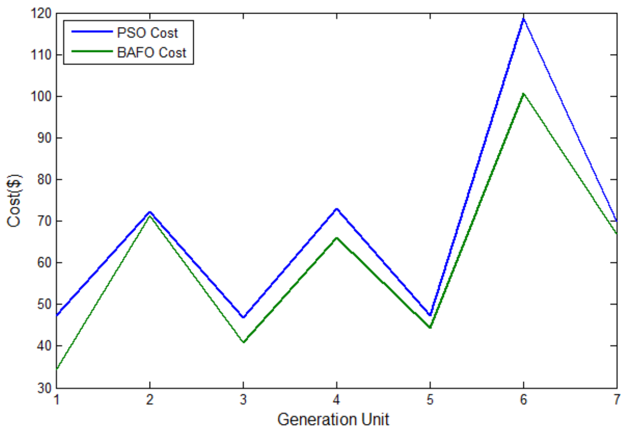


Fig. 1.3 Compression of fuel cost with BFO and PSO

CONCLUSION

In this research paper, application of Bacterial Foraging Optimization algorithm is presented for the solution of local convex economic load dispatch problem of electric power system. The performance of Bacterial Foraging Optimization algorithm is tested for all types of power plants. The effectiveness of proposed Bacterial Foraging Optimization algorithm is tested with the 7 generating unit's model considering Stochastic Economic Load Dispatch using Pareto Distribution. The simulation results show that Bacterial Foraging Optimization has been successfully implemented to solve different ELD problems moreover, BFO is able to provide very spirited result in term of minimizing total fuel cost. Also, the convergence of BFO is very fast as compared to Particle Swarm Optimization (PSO) algorithm, power systems. Also, it has been observed that the BFO has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics than other widespread techniques reported in the recent literature.

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