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Optimal Thermal Generating Unit Commitment via Evolutionary Algorithms: A Review

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Abstract
This paper presents a literature survey of economic load dispatch problem. The economic load dispatch (ELD) is one of the most important optimization problems of electrical power system. The aim of the ELD problem is to determine the power productions of total generating units from a system in order to have minimum fuel cost, and to meet the all constrains. Solving ELD involves conveying a precise model of optimization and then selecting an appropriate optimization technique. The simplest model for the ELD problem is one in which the fuel cost of the generating units is quadratic in nature, and with two constraints only: the equality and inequality constraints, respectively; the generators operate between the minimum and maximum limits of power. However, the more practical features of the operational units, the precise model is improved by considering the valve-point effects and by presenting the constraints like ramp rate limits, prohibited zones, the transmission losses; it introduces a non-linear, non-smooth and non-continuous accurate model of optimization. To solve the ELD problem, several methods, classic or based on artificial intelligence, have been used over time. Several soft computing methods like particle swarm optimization (PSO), artificial bee colony (ABC), ant colony optimization (ACO), simulated annealing (SA), genetic algorithm (GA), etc. are now being applied to find even better solution to the ELD problem. An interesting trend in this area is application of hybrid approaches like GA-PSO, ABC-PSO, CSA-SA, etc. and the results are found to be highly competitive.

Keywords: *ELD, ramp rate limit, valve point loading effect, transmission loss*

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INTRODUCTION

During last ten years, electrical power market became broader and more competitive. Main aim of electrical power market is to generate more electrical power at lower cost. It requires better planning and better power system operation and control. ELD problem can be solved for smooth, the way towards power system and for economic operation. If load dispatch is best, then it can reduce the production cost and hence increase the system reliability and can maximize the energy capability of thermal units.

ELD problem is a non-linear optimization problem which can be solved to minimize the fuel cost and maximize the electrical power output with the satisfaction of all the power system constraints like ramp rate limits, prohibited zones, transmission losses etc. Since ELD is not a linear problem, hence ELD problems cannot be solved by using any classical method. To solve such non-linear problem, we require an optimization tool.

In last few years, many genetic algorithms have been applied to solve ELD problems. In practical area of large power system, there are large generators and turbines, and these have highly non-linear and discontinuous type of input-output characteristics due to the valve point loading effect. Due to non-linear characteristics of thermal units, classical methods fail to solve ELD problems. Though dynamic programming is not affected by non-linearity and discontinuity of the cost curves but it suffers from the expletive of dimensionality and local optima. Among all other intelligence methods neural network base method is more successful method to solve ELD problems. However, some neural network methods have slow convergence and more iteration. Due to parallel search technique of evolutionary algorithms (Genetic algorithm, evolutionary strategy and evolutionary programming), these are fast in operation than simulated annealing. For solving ELD problems EAs are the better choice, since these have better constraint handling capability, are robust, and require less information and global search capability.

For developing reliable and fast solution of ELD problems, evolutionary algorithms are still an area of researchers in power system. A better solution of ELD problems may result more economic benefits. Some meta-heuristic algorithms have been proposed like, artificial bee colony [1], differential evolution [2–5], harmony search (HS) [6, 7], particle swarm optimization (PSO) [8–16], genetic algorithm (GA) [18], ant colony search optimization (ACO) [19], bacterial foraging (BF) [20], biogeography based optimization (BBO) [21] and teacher learner based optimization (TLBO) [17] for alternative solution of ELD problems.

Recently, for developing better solution some modifications have been made in the above population based methods like, Secui proposed a modified artificial bee colony for economic dispatch on 6, 13, 40, 52-unit system with valve-point effects and transmission losses [1]. Sayah presented a hybrid differential evolution based on particle swarm optimization for non-convex economic dispatch problem with non-linear constraints like valve-point loading effect, ramp rate limits and prohibited operating zones [4].

Amjady presented a modified differential evolution for solution of non-convex economic dispatch problem [5]. Qun applied hybrid harmony search with arithmetic crossover operation for economic dispatch [6]. Wang proposed a differential harmony search algorithm [7], Zhang proposed hybrid bare-bones PSO for dynamic economic dispatch problem with valve-point loading effects [10]. Niu presented a cultural PSO [11], Safari applied iteration PSO [12], Basu presented a modified PSO [13], Hosseinnezhad presented θ-PSO for smooth and non-smooth cost function [16], and Vu presented a weight-improved PSO for economic dispatch based on improving the function of weight parameters [9].

PROBLEM STATEMENT

Objective Function

Main objective of economic load dispatch problem is to minimize the production cost of electrical power and meet the load demand of an electrical power system with satisfaction of constraints. The objective function of ELD problem is given under where Eq. (1) presents combined convex and non-convex fuel cost and Eq. (2) is cubic in nature:

$$Min\ F_t = \sum_{i=1}^{m}[(a_i \times P_i^2 + b_i \times P_i + c_i) + |d_i \sin[(P_i^{min} - P_i)]\,|] \quad (\$/h) \qquad (1)$$

$$Min\ F_t = \sum_{i=1}^{m}(a_i + b_i \times P_i^1 + c_i \times P_i^2 + d_i \times P_i^3) \qquad (\$/h) \qquad (2)$$

Here $a_i , b_i , c_i , d_i\ and\ e_i$ are the cost coefficients of i^{th} Generator, m are the number of units in the system.

Constraints

Power Balance Constraints

$$\sum_{i=1}^{m} P_i - P_D = P_L \qquad (3)$$

Here P_D is the total load demand, and P_L is the total transmission loss.

Transmission losses using B-coefficients are given by:

$$P_{Loss} = \sum_{i=1}^{m}\sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{oi} P_i + B_{oo} \qquad (4)$$

Ramp Rate Limits

$$-RRL_{id} \le P_i^t - P_i^{t-1} \le RRL_{iu} \qquad (5)$$

Where RRL_{id} and RRL_{iu} are the ramp down and ramp up limits of the ith generator respectively.

Prohibited Operating Zone

$$P_i^{min} \le P_i \le \underline{P}_i^1$$
$$\overline{P}_{i,k-1}^{u} \le P_i \le \underline{P}_{i,k}^1 \quad k=2, 3\ldots\ldots, n_Z \qquad (6)$$
$$\overline{P}_{i,n_i}^{u} \le P_i \le P_i^{max}$$

Here, n_i is the number of prohibited zones, and $\underline{P}_{i,k}^1, \overline{P}_{i,k-1}^{u}$ are the upper and lower POZ limits.

Generation Limits Constraints

$$P_i^{min} \le P_i \le P_i^{max} \qquad (7)$$

Here P_i^{min} is minimum power of i^{th} generator and P_i^{max} is the maximum power of i^{th} generator.

SOLUTION METHODOLOGIES

Genetic Algorithm

The GA is mainly an evolutionary algorithm, several of the others of its kind being evolution strategies, genetic programming, and EP. An evolutionary algorithm sustains a population of candidate solutions to an optimization problem. The population changes through repetitive application of stochastic operators. Just as a new generation of a population is promoted by elimination of useless individuals and by developing useful features, a new and better solution is found by iterative fine-tuning of fitness function. Generally, GA move in a loop with an initial population formed with a set of individuals generated randomly, in each iteration new population is created by applying a number of stochastic operators to the earlier population due to genetic crossover and mutation.

Oreo and Irving presented a hybrid genetic algorithm solution method that incorporated a fast priority list heuristics generator ordering scheme to speed up the GA for solving large scale economic load dispatch problem in power system [18].

Particle Swarm Optimization

In 1995, Kennedy and Eberhart introduced particle swarm optimization (PSO) based on the social behaviour of particles in the swarm such as bird herding and fish training. PSO searches in parallel fashion using a group of particles. Each particle represents a candidate solution to the problem. In PSO, particles change their positions or states with time and fly around in a multidimensional search space. Each particle moves towards the optimum point based on its present velocity, its previous experience and the experience of its neighbours.

Each particle has two characteristics, position and velocity; each particle walks in the search space and remembers the best position obtained so far. Particles communicate their information to each other and adjust their individual speed and velocity based on information received on best position.

Ant Colony Optimization

Ant colony optimization is another dominant swarm-based optimization technique often used to solve the ELD problem. The algorithm follows ant's movement in search of food. The ant that reaches the food in shorter path returns to the nest earlier. Other ants in the nest have high probability of following the shorter route because pheromone deposited in shorter path is more than that deposited by ants traversing longer paths.

Table 1: *Various Hybrids PSO Based Results of 13 Unit System with 1800 and 2520 MW Demand.*

Unit	WIPSO [9]	PSOGSA [15]	θ-PSO [16]
P_1 (MW)	538.5587	628.3185	628.3185
P_2 (MW)	150.4425	299.1993	149.5978
P_3 (MW)	224.3995	299.1993	222.7512
P_4 (MW)	109.8665	159.7331	109.8665
P_5 (MW)	109.8665	159.7331	109.8665
P_6 (MW)	109.8665	159.7331	109.8665
P_7 (MW)	109.8665	159.7331	109.8665
P_8 (MW)	109.8665	159.7331	60.0000
P_9 (MW)	109.8665	159.7331	109.8665
P_{10} (MW)	77.3999	107.4843	40.0000
P_{11} (MW)	40.0000	75.0000	40.0000
P_{12} (MW)	55.0000	60.0000	55.0000
P_{13} (MW)	55.0000	92.3999	55.0000
Total cost($/h)	17,968.946677	24252.9362294	17,963.8297
Power output (MW)	1800	2520	1800

In ACO algorithm, a number of search trials, analogous to ants, work comparable to find the best solutions of the ELD problem. An ant develops a solution and shares the information (pheromone) with other ants. Though each ant can form a solution, improved solutions are established through this information exchange within an organizational zone.

Pothiya *et al.* presented a solution of economic load dispatch with non-smooth cost function using ant colony optimization [19].

Harmony Search

Harmony search (HS) is an evolutionary algorithm that copycats musician's behaviour such as random play, memory-based play and pitch adjusted play to get a perfect state of harmony. The typical HS comprises there main operations: random search, memory consideration and pitch adjustment.

QunNiu *et al.* investigated a successful adaption of modified harmony search with opposition based learning (OBL) to solve ELD problems with various constraints including valve point effects, multi-fuels, ramp rate limit, combined heat ELD problem and prohibited operation zones [6].

Bacterial Foraging

BF algorithm has been broadly accepted as a novel optimization algorithm for distributed optimization and control. BF is based on communal and supportive behavior found in nature. The foraging behavior of bacteria can be modeled as an optimization method where every bacteria efforts to maximize its gained energy per each unit of time expended on the foraging process and avoiding toxic ingredients. Besides, swarm search assumes communication among individuals. The BF algorithm begins with formation of an initial population. The size of the initial population is equal to the number of bacteria and all the bacteria undergo various stages iteratively in order to reach a global optimum.

Elattar investigated a successful adaption a hybrid genetic algorithm and bacterial foraging to solve ELD problems with various constraints including valve point effects, ramp rate limit and prohibited operation zones and including losses [20].

Biogeography based Optimization

Biogeography concerns immigration of species from one space to another, evolution of new species, and elimination of existing species. A habitat is any space that is geographically remote from another area. Habitats with a high habitat suitability index (HSI) lean towards to large number of species, whereas those with low HSI have a small number of species. Habitats by means of a high HSI have a low immigration rate and a high emigration rate of species since they are overpopulated. Quite the opposite, habitats with a low HSI have a high immigration rate and low emigration rate because of their sparse population of species.

Bhattacharya and Chattopadhyay examined a solution of ELD using biogeography based optimization with various constraints including valve point effects, ramp rate limit and prohibited operation zones and including losses [21].

Artificial Bee Colony

ABC algorithm is a swarm-based met heuristic algorithm pretending the behaviour of honeybees. Employed bees have the role of exploiting the recognized food sources and then sharing various pieces of information with other bees waiting in the hive to make a good possible decision while choosing a food source. ABC comprises three bees namely, employed bees, onlooker bees and scout bees. In ABC, the following resembling is made: food source position resembles the possible solutions of optimization problem and the quantity of food resembles value of fitness function.

Secui investigated modified ABC with introduction of new relation to update the solutions within the search space, in order to increase the algorithm ability to avoid premature convergence and to find stable and high quality solutions to ELD problems with valve-point effects and transmission losses [1].

Differential Evolution

Differential evolution is a population-based stochastic parallel search method in general framework of evolutionary algorithms. DE is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Such methods are commonly known as Meta heuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions.

DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means that DE does not require the optimization problem to be differentiable as is required by classic optimization methods such as gradient descent and Quasi-Newton methods. DE can therefore also be used on optimization problems that are not even continuous, are noisy, change over time, etc.

DE initializes with an initial population of possible solutions (parents) and produces new solutions (child) via three chromosomal operators-mutation, crossover, and selection until the optimal solutions are reached.

Table 2: *Various Hybrids DE Based Results of 40 Unit System with 10500 MW Demand.*

Methods	MDE [5]	DEPSO [4]	CDEMD [3]
Min cost ($/h)	121414.79	121,412.56	121423.4013
Max cost ($/h)	121466.04	121,468.25	N.A
Average cost ($/h)	121418.44	121,419.31	N.A
S.D*	N.A*	110.06	N.A
CPU (s)	N.A	21.52	N.A

S.D.= Standard Deviation, N.A.= Not Available.

Teaching Learning Based Optimization
TLBO is based on the association between the teacher and student in the class. It is influenced by the guidance of a teacher upon the outcome of learners in a class. It is a population based method and like other population based methods it uses a population of solutions to get the global solution. A group of learners create the population in TLBO. Every optimization method has numbers of different design variables. The various design variables in TLBO are denoted as different subjects offered to learners and the learners' result in that particular subject is analogous to the fitness, like in other population-based optimization methods. As per the society, teacher is the most learned individual; the finest solution is equivalent to teacher in TLBO. The algorithm of TLBO has two portions. The first portion comprises of teacher phase and the second portion comprises of learner phase. The teacher phase means learning from the teacher and the learner phase means learning through the communication among students in a class.

Banerjee *et al.* investigated TLBO to find quality solutions to ELD problems with valve-point effects [17].

Chemical Reaction Algorithm
CRO roughly mimics what occurs to molecules in a chemical reaction system. Each chemical reaction be likely to release energy, consequently, the products usually have less energy than the reactants. In terms of stability, lesser the energy of the matter, the more stable it is. In chemical reaction, the primary reactants have high-energy and they are more unstable, pass over some energy obstacles and become the final products in low-energy stable states. Consequently the products are always more stable than the reactants. It is not tough to discover the mimic between optimisation and chemical reaction. Both of them objective to search for the global optimum with detail to different objectives and the process grows in a step wise manner.

Roy *et al.* examined CRO to find ELD problem solutions with valve-point effects and ramp rate limits [22].

CONCLUSIONS
The ELD problem may be generally classified as convex and non-convex. In convex ELD input-output characteristics are assumed linear, whereas in non-convex ELD problem having discontinuous and nonlinear characteristics are subjected to various constraints (valve-point effect, transmission losses, ramp rate limits, and prohibited operating zones). In this review paper, several solution techniques of optimal thermal dispatch via evolutionary algorithms are studied for economic load dispatch problem. There are many hybrid algorithms, which are being used now days, some of them are studied in this paper, and corresponding results have been shown prior to conventional algorithms.

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