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Review on Evolutionary Computing Techniques in Power System for Economic Load Dispatch

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Abstract: The prime focus of the concept economic load dispatch (ELD) is one of the main functions of modern energy management system, which determines the optimal real power setting of generating units with an objective to minimize total fuel cost of thermal plants.Soft computing is the approach to artificial intelligence and it has showed an excellent performance in solving the combined optimization problems. In this paper, issues related to the Study of the soft computing techniques are highlighted for a successful application to solve economic dispatch problem, which is a constrained optimization problem in power systems. Economic dispatch problem is a major problem where objective function is highly non-convex, non-linear, non-differentiable and may have multiple limited minima. Therefore, classical optimization methods may not converge or get trapped to any local minima. The purpose of this work is to find out the advantages of application of the soft computing technique to the economic load dispatch problem.

Keywords: - Ant colony optimization, bacteria foraging optimization, economic dispatch, evolutionary algorithm, genetic algorithm

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I. INTRODUCTION

The basic object of the electrical power system is to perform the operation with maximum reliability limits with minimum production cost Economic Dispatch (ED) is defined as the process of allocating optimal power generation levels to each of the generating units in the station, so that the entire supply demand can be meet in a most economically manner. In case the load is fixed (i.e. static economic dispatch), the objective is to calculate, for a single period of time, the output power of every generating unit .Unfortunately the load of a power system is always changing, so the generators correspondingly respond i.e. with increase in the load the generator produces more power and vice-versa. This entails for optimal allocation of generators participation in sharing the load at the current interval of time to meet the forecasted load demand for the same interval. As per our definition, economic load dispatch is a means that allows the generators active power to vary within coordinate. The objectives of this study are as follows

1. To minimize the generation cost
2. To minimize the total power loss in the Power System network,
3. To minimize the voltage (and/or current) deviations, and
4. To maximize the quality of the power supplied to the customers

Mainly the economic load dispatch is kind of on-line process to allocate the generating units in which load is distributed in such a manner as the total operating cost of each generating unit fulfilling the system equality and inequality constraints [6]. While the demands of load roll constantly. Therefore on minimum cost, very hard to fulfill the load demands. By consider all the system constraint to determine the optimum solution for scheduling the available generating unit is the major concern of the Economic Dispatch in Power System. Numerous traditional optimization techniques like lambda iteration method [13], gradient method [14-15], Newton's method [16-17], linear programming, Interior point method and dynamic programming generally used to resolve the fundamental economic dispatch problem. In Lambda iteration method the major difficulty is to adjust lambda for complex cost functions. In Gradient methods the problem of convergence is the present with inequality constraints. The Newton's method is sensitive for the selection of initial conditions. Linear programming gives the optimal solution in very less calculation time period but its results are not precise due to the problem of linearization[5][7].In Interior point method[18-19] if the step size not chosen properly it may give the incorrect solutions although this method is comparatively faster than the linear programming.

Dynamic programming rise difficulty from curse of dimensionality. Many of the traditional optimization methods required derivative information of the objective function to find the search track. But actual fuel cost functions are non-linear, non-convex and non-differentiable because of ramp rate limits, prohibited operating zones, valve point effects and multi-fuel options. Recently some heuristic techniques such as genetic algorithm [43] combined with simulated annealing; evolutionary programming, improved tabu search, ant swarm optimization, artificial bee colony [44] and particle swarm optimization have been used to solve the complex non-linear optimization problem.

II. ECONOMIC DISPATCH (ED) PROBLEM

Economic Dispatch is the important optimization problems in power system network, which is used to decide the best combination of power outputs of all generating units to diminish the entirety fuel cost while fulfilling various constraints over the whole dispatch periods.[1] The traditional or static ED problem assumes constant power to be supplied by a given set of units for a certain time and attempts to reduce the cost to supply this energy subject to constraints on the static behavior of the generating units like system load demand. Shortly, static ED determines the loads of generators in a system that will meet a power demand during a single scheduling period for the least cost[8][9][13]. Therefore, it might fail to capture large variations of the load demand due to the ramp rate limits of the generators [20][38]. Due to large variation of the customers load demand and the dynamic nature of the power systems, it became necessary to schedule the load beforehand so that the system can predict impulsive changes in demand in the future. Dynamic ED is an extension of static ED to determine the generation schedule of the committed units so that to meet the predicted load demand over the entire dispatch periods at minimum operating cost under ramp rate and other constraints. The ramp rate constraint is a dynamic constraint which used to maintain the life of the generators, i.e. plant operators, to avoid shortening the life of the generator, try to keep thermal stress within the turbines safe limits. Though the violations of the ramp rate limitations are assessed by examining the generators output over a given time period, this problem cannot be solved for a single value of MW generation. The dynamic ED [21] is not only the most accurate formulation of the economic dispatch problem but also the most difficult to solve because of its large dimensionality. The DED difficulty is usually solve by discretization of the total dispatch period into a numeral of small time intervals, in which the load demand is implicit to be constant and the system is considered to be in a sequential steady state. Over each time interval a static ED problem is solved under static constraints and the ramp rate constraints are enforced between the consecutive intervals. In the DED problem the optimization is done with respect to the dispatchable powers of the units [10][12].

III. MODIFIED TRADITIONAL TECHNIQUE

The conventional forecasting techniques have been customized and modified so that they are capable to robotically correct the parameters of forecasting model under varying environmental situation. Some of the techniques which are the modified version of these traditional techniques are adaptive load forecasting, stochastic time series and support vector machine based techniques. [2]

3.1. Adaptive Demand Forecasting

Demand forecasting model parameters are inherently corrected to keep record of the shifting load conditions. Hence Demand forecasting is adaptive in nature and can also be used as an on-line software package in the utilities control system. Next state vector is estimated using current prediction error and the current weather data acquisition programs [22]. State vector is determined by total historical data set analysis. Switching between multiple and adaptive regression analysis is possible in this mode. The similar model as in the multiple regression section, given below equation is used in this model.

$$Y(t) = Xt\ at + et,$$

Where, t-sampling time, Y(t)- measured system total load, Xt -vector of adapted variables such as light intensity, temperature, time, wind speed, humidity, day type (workday, weekend), etc., at -transposed vector of regression coefficients and et-Model error at time t.

3.2. Stochastic Time Series

The Time series methods appear to be among the most popular approaches that applied to STLF [23]. The time series methodologies are based on the assumption that the data have an internal structure, such as autocorrelation, trend or seasonal variation. The primary impetus of the method is to correctly accumulate a pattern corresponding to available data and then find the forecasted value with respect to time using the established model. The next subsection discusses some of the time series models used for load forecasting [24].

3.2.1 Auto Regressive (AR) Model

Auto-Regressive (AR) model can be used to model the load profile, If the load is assumed to be a linear combination of previous loads, which is given by:

$$Lk = \sum_{i=1}^{m} \alpha ik\, Lk\text{-}i + ek$$

Where, Lk is the predicted load at time k (min), ek is a random load disturbance, αi, i =1……m are unknown coefficients and above given equation is the auto regressive model of order m [25].

3.2.2 Autoregressive Moving-Average (ARMA) Model

ARMA model represent the present value of the time series y (t) linearly in terms of its values at prior periods [y(t-1), y(t-2),..] & in terms of previous values of a white noise [a (t), a (t-1)…]. For an ARMA of order (p, q), the model is written as:

y(t) = φ1y(t -1)+…+ φpy(t-p)+a(t)- φ1a(t-1)-…- φq(t-q).

A recursive scheme is used to identify the parameters, or using a maximum-likelihood approach [23, 25].

IV. SOFT COMPUTING TECHNIQUES

In present research scenario soft computing techniques are very prominent, efficient and effective to deal the complex economic dispatch solutions. It has been very widely in use over the last few decades. A soft computing technique provides a promising approach which runs in parallel with the human mind to find solution and learn from the environment ambiguity and vagueness. It is fast emerging as a tool to help computer-based intelligent systems mimic the ability of the human mind to employ modes of reasoning that are approximate rather than exact. The soft computing constitutes a collection of disciplines which include fuzzy logic (FL) [27], neural networks (NNs) [28], and evolutionary algorithms (EAs) like genetic algorithms (GAs) etc [2]. Natural intelligence is the product of millions of years of biological evolution. Simulating complex biological evolutionary processes may lead us to discover, how evolution propels living systems toward higher level of intelligence. One of the newer and relatively simple optimization approaches is the GA which is based on the evolutionary principle of natural selection. Perhaps one of the most attractive qualities of GA is that it is a derivative free optimization tool.[4] The demand/ load forecasting techniques are also developed based on the following soft computing/ intelligent techniques. The Knowledge-based expert systems have been utilized for this purpose also.

4.1 Genetic Algorithms

The genetic algorithm (GA) [29] [41] or evolutionary programming (EP) approach is used to identify the autoregressive moving average with exogenous variable model for load demand forecasts. By simulating natural evolutionary process, the algorithm offers the capability of converging towards the global extreme of a complex error surface [10]. It is a global search technique that simulates the natural evolution process and constitutes a stochastic optimization algorithm. Since the GA [42] simultaneously evaluates many points in the search space and need not assume the search space is differentiable or unimodal, it is capable of asymptotically converging towards the global optimal solution, and thus can improve the fitting accuracy of the model. The general scheme of the Genetic Algorithm process is briefly described here. The integer or real valued variables to be determined in the genetic algorithm are represented as a D-dimensional vector P for which a fitness f (p) is assigned [30]. The initial population of k parent vectors Pi, i = 1, k, is generated from a randomly generated range in each dimension. Each parent vector then generates an offspring by merging (crossover) or modifying (mutation) individuals in the current population. Consequently, 2k new individuals are obtained. Of these, k individuals are selected randomly, with higher probability of choosing those with the best fitness values, to become the new parents for the next generation. This process is repeated until *f* is not improved or the maximum number of generations is reached.[8]

4.2 Biogeography-Based Optimization Algorithm (BBO) Technique

In BBO, the migration operation refers to the process of either entering or leaving of the species into or from an island [8]. Like PSO and other population based search techniques, [46] BBO [26] [31] [39] also uses a population of candidate solutions for optimization purpose. Representation of each candidate solution is done as a vector of real numbers. Here each real number in the population is considered as one suitability index variable (SIV). In ED problem, these SIVs are analogous to the power output of the generators. The SIVs in one array are used to calculate the habitat suitability index (HSI) of a habitat. The HSI is analogous to the objective function as used in other techniques. In ED problem, the HIS is analogous to the generation cost of a generator. Solutions with high HSI represent a superior solution whereas solutions with low HSI represent an inferior solution. The process of species entering a habitat is known as immigration whereas the process of leaving a habitat is known as emigration. The colonization rate, λ and the evacuation rate, μ of each habitat is used to probabilistically share information with other habitats/solutions. Every result of solution is customized according to probability $Pmodify$, which is known as the habitat modification probability, based on other solutions. If a any habitat is chosen for modification, then its λ is used to probabilistically come to a decision whether or not to modify each SIV of that habitat. If a particular SIV in a given habitat is selected for modification, then μ of other habitats are used to probabilistically decide which of the habitats should migrate a randomly selected SIV from those habitats to that particular habitat. Unlike other AI techniques where the recombination process is used to generate a completely new solution, the migration operation in BBO is used to bring changes within an existing solution [40]. In order to prevent the best solutions from being changed by the migration process, few elite solutions are kept the same in the consequent iterations. Immigration and emigration rate of particular habitat which contains n species is given as

$$\lambda_n = \mathrm{I}\,(1 - n/N)$$
$$\mu_n = E_n/N$$

I, *E*: the maximum immigration and emigration rates respectively.
N: maximum number of species that a habitat can contain.[4]

4.3 Bacteria Foraging Optimization (BFO)

BFO [32][45] method was motivated by the natural selection which tends to eliminate the animals with poor foraging strategies and favor those having successful foraging strategies. The foraging strategy is governed by four processes namely Chemotaxis, Swarming, Reproduction and Elimination & Dispersal [10].

4.3.1 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 it starts 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, θi (j, k, l) is the position of i^{th} bacteria at j^{th} chemotactic step, k_{ith} reproduction step and l_{th} elimination dispersal event. The position of the bacteria in the next chemo tactic step after a tumble is given by:

$$\theta_i(j+1,k,l) = \theta_i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

Where
C (*i*) denotes step size;
Δ (*i*) random vector;
Δ*T* (*i*) transpose of vector Δ (*i*).
If the health of the bacteria improves after the tumble, the bacteria will continue to swim to the same direction for the specified steps or until the health degrades.

4.3.2 Swarming:

Bacteria exhibits swarm behavior i.e. healthy bacteria try to attract other bacterium 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

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{S} J_{cc}^{i}(\theta, \theta_i(j,k,l))$$
$$= \sum_{i=1}^{S}[-d_{attract} exp(-w_{attract}) \sum_{m=1}^{p}(\theta^m - \theta_i^m)^2]$$
$$+ \sum_{i=1}^{S}[-h_{repelent} exp(-w_{repelent}) \sum_{m=1}^{p}(\theta^m - \theta_i^m)^2]$$

Where Jcc = the relative distances of each bacterium from the fittest bacterium, S = number of bacteria, p number of parameters to be optimized, θm position of the fittest bacteria, $d_{attract}$, $w_{attract}$, $h_{repelent}$, $w_{repelent}$ different parameters[33][34].

4.3.3 Reproduction

In this step, population members who have had sufficient nutrients will reproduce and the least healthy bacteria will die. The healthy and better population replaces an unhealthful bacterium which gets removed owing to their poor foraging abilities. This makes the population of bacteria constant in the evolution process [33][34].

4.3.4 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. abolition and diffusion helps in dropping the behavior of stagnation i.e. being ensnared in a impulsive solution point or local optima[32-34].

4.4. Ant Colony Optimization (ACO)

ACO [35] was inspired by the foraging behavior of ant colony. While moving, each ant lays certain amount of pheromone on the path. Ants use the pheromone trails to communicate information among the individuals and based on that each ant decides the shortest path to follow. ACO technique has been successfully used for difficult discrete combinatorial optimization problems such as Traveling Salesman Problem, Sequential Ordering, Routing in communication problems, etc.[12] The algorithm consists of four stages: Solution construction, Pheromone update, Local Search and Pheromone Re-initialization[37].

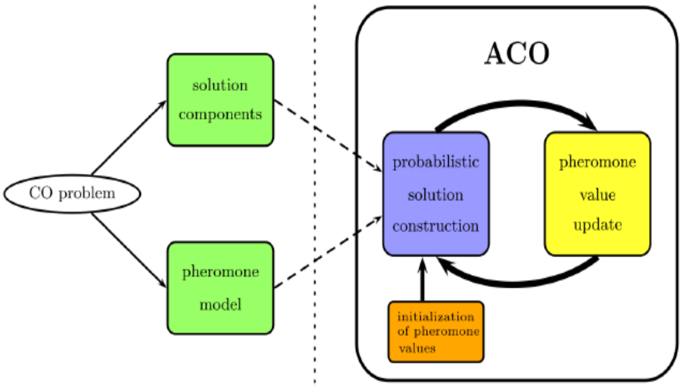

Fig. 1. The working of the ACO.

The basic way of working of an ACO algorithm is graphically shown in Fig. 1. Given a CO problem to be solved, one first has to derive a finite set C of solution components which are used to assemble solutions to the CO problem. Second, one has to define a set of pheromone values T. This collection of values is usually called the pheromone model, [13] which is technically taken into account as a parameterized probabilistic model. In general, the ACO approach attempts to solve an optimization problem by iterating the following two steps:

- Candidate solutions are structured using a pheromone model, which is, a parameterized probability distribution over the solution space;
- The candidate solutions are used to modify the pheromone values in a way that is deemed to bias future sampling toward high quality solutions.

V. CONCLUSIONS

In this paper a comparative study of different evolutionary techniques to solve the power system ED problem is investigated. Different techniques namely; regression, multiple regression, exponential smoothing, iterative reweighted least squares, ARIMA model, ARMA model, stochastic time series- autoregressive, adaptive load forecasting, support vector machine based, soft computing based models- genetic algorithms, in this paper it is clear that solution quality and robustness of RCGA is better than BCGA. Convergence characteristics of ACO and BFO are attractive and they converge quickly but solution quality is not as good as PSO or GA. From all these findings, it can be concluded that PSO outperforms the others for the chosen set of parameters for solving the Economic Dispatch problem.

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