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Optimization of Load Flow with Economic Dispatch Using PSO

Mr. Girish K. Mahajan[1] and Dr. E. Vijay Kumar[2]

PHD Scholar, Department of Electrical Engineering, Radhakrishanan Univesity, MP, Bhopal[1]

HOD, Department of Electrical Engineering, RKDF Institute of Science & Technology, MP, Bhopal[2]

Abstract: *Under normal operating conditions, the generation capacity is more than the total load demand and losses. The objective is to find the real power scheduling of each generator for an interconnected power system under testing condition to minimize the operating cost of the power plant. Hence the generators power is allowed to vary within the given limits to meet the particular load with minimum fuel cost which is called as optimal power flow problem. The objective function of this research is to minimize the fuel cost of the power system for the various loads under consideration by solving the economic dispatch problem (EDP) of real power generation by using MPSO optimization algorithm. We compares the optimization techniques such as Particle Swarm Optimization, Modified Particle Swarm Optimization (MPSO) in a 3-unit generating system to show the effectiveness of the MPSO algorithm. Also by using the optimization technique the power losses of the considered power system were reduced. In the Particle Swarm Optimization (PSO) on the optimization of the power flow in a IEEE system with 30 nodes, which has some nodes with distributed generation. In first place, the mathematical model used for the optimization of the electricity generation costs. Afterwards, this model is applied in a case study with a IEEE system with 30 nodes. The results obtained through PSO are compared to other optimization methods, demonstrating that the cost and losses for the 30-node system are less than the values delivered by other methods. Then the same model is applied for the same power system with distributed generation in some of their nodes.*

Keywords: PHEV, MPPT, EVs, FCSs, MPPT, VSC, HC, HBC

I. Introduction

1.1 Overview

In a competitive environment, a precise mathematical model is often needed to optimize the cost of production, therefore, he found several techniques, classic and modern, that were used to solve this optimization problem as reported in [1].Among the classical methods are the Newton-Raphson method, the iterative lambda method, the base point and the factor of participation method. But the confusion that arises for these techniques is that the cost function is a non-functional function. Linear with several minimums, which makes it difficult for these algorithms to determine the overall minimum, this leads to non-optimal solutions, so the examination of the nonlinear characteristics of these plants requires very robust algorithms to avoid finding themselves at the local optimum. Therefore, traditional computational-based techniques fail to solve this type of problems [1].

Over the last decade, several modern computer-based techniques have been proposed based on artificial intelligence to overcome some of the difficulties encountered in modeling and solving the non-linear problem of economic dispatching. In fact, artificial intelligence techniques have given good results in comparison with classical techniques, because they allow a precise modeling of the problem as reported in [1].

These intelligent tools, which are quite successful in solving different classes of problems, can be classified into the following groups:

- Expert system (ES)
- Fuzzy logic (FS)
- Artificial Neural Networks (ANN)

- Simulated Annealing (SA)
- Tabu Search (TS)
- Genetic Algorithm (GA)
- Evolutionary Programming (EP)
- Particle Swarm Optimization (PSO)

An expert system consists of two parts, an inference engine and a database. The inference engine controls the user interface, external folders, program access and scheduling. The database contains information that is specific to a particular problem. This database allows an expert to define the rules that govern the process. An ES model is applied primarily to reduce the time of solution for it avoids the use of complex mathematical calculations. But, it fails, if the new load model is not similar to that stored in the dynamic database. However, the SE still found significant success in some applications such as fault diagnosis as reported in [1].

Lotfi A. Zadeh presented the set theory scrambled in 1965 and later he developed his ideas and presented the concepts of a linguistic variable and scrambles if then the rules in1973. This work has created the foundation for fuzzy logic control and most of the common applications of fuzzy logic are in areas that may only represent inaccurate or uncertain data. Scrambled systems use an approximate reasoning mode and allow these systems to make decisions based on vague and unfinished information in a manner similar to human beings. The binary logic of expert systems describes and manipulates the exact concepts while scrambled systems allow uncertainties in problem formulation to be expressed and processed. Interest in the scrambled expert system has grown considerably over the last few years and considerable developments have taken place to solve problems involving multiple conflicting objectives. Reduced computing timemakes these adaptive scrambled systems more suitable for Real-time applications. But these methods can lead to unwanted solutions in certain situations such as sudden load demands. In addition, these methods are not completely free of mathematical complexity as reported in [1].

Artificial Neural Networks are powerful techniques for solving many of the world's real problems. They have the ability to learn from experience to improve their performance and adapt to changes in the environment. They can also process unfinished information or noisy data. In addition they can be very effective especially in situations where it is not possible to define the rules or steps that lead to the solution of a problem. Essentially, ANN is an information processing system, which can be considered a black box that can predict a performance model when it identifies a given input model. Once qualified, the neural network can identify similarities once presented with a new input model, resulting in a predicted performance model. Another significant benefit is in ANN interpolation capabilities to produce appropriate results for noisy and unformed inputs. One of the most important aspects of the neural network is learning. The study can be done in a managed or unsupervised way. In directed training, inputs and outputs are provided. The network then processes the inputs and compares its resulting outputs to the desired outputs as reported in [1].

Errors are then calculated and then used to adjust the weights to control the network. This process occurs repeatedly as the weights are continually twisted. In unsupervised training, the network is equipped with inputs but no desired outputs. The system itself then decides on how to group the input data. This is often referred to as the self-organization or adoption as reported in [1].

Because of their simplicity as well as the ability to execute hardware most ANN applications in electrical power systems use the perception multilayer model based on the back propagation algorithm (boiling point) for Training. Despite their popularity the boiling point algorithms suffer from convergence difficulties due to local minima due to the fact that the conventional ANN is highly non-linear in their parameters and the study is based on nonlinear optimization techniques like the steepest descent technique. The other main disadvantage of ANN has to find an optimal configuration because no exact rule is known to decide the number of hidden layers, the number of neurons in each layer and the type of activation work in each layer. Avoiding these drawbacks of booster-based neural networks, a new generation of ANN, based on the theory of radial basis function (RBF) for approximations, has been developed. These ANNs, called the ANN radial basis function or simply the RBF Networks, have self-configuring architecture and are much faster and more reliable than boiling point networks. During the last two decades, ANN had received considerable attention and a large number of papers on their application to solve the problem of the feeding system was

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documented as reported in [1].

More recently, it has been found that stochastic soft optimization techniques such as simulated annealing, Tabu searching, genetic algorithm, evolutionary programming and particle swarm optimization are quite effective in strongly solving the non-linear problems of ELD because there is no restriction to the shape of the fuel cost functions. Although these heuristic methods do not always guarantee the globally optimal solution, they generally provide a comprehensive solution fast and reasonable. Kirkpatrick's, and others, proposed the basic concept of the simulated annealing algorithm in 1983. The optimization process in the SA technique is essentially a simulation of the annealing processof molten metals. From a high temperature, a molten metal is cooled slowly until it is solidified at a low temperature. The number of iterations in the SA algorithm is analogous to the temperature level. In each iteration, a candidate solution is produced. If this solution produced is a better solution, it will be refined to generate yet another solution of candidate. If this is a deteriorated solution, the solution will be accepted when its probability of acceptance is greater than a random number produced between 0 and 1. The solution process is allowed to continue until the number maximum iterations is achieved or the optimum solution is found.SA is a relatively straightforward technique to implement and it was first applied to the economical shipment of load by KP Wong and others as reported in [1].

However, the SA annealing program should be tuned carefully otherwise the realized solution will always be locally optimal. Therefore, the proper arrangement of the appropriate control parameters of the SA based technique is a difficult task and the speed of the algorithm often becomes slow as a proper annealing program needs the enormous computer moment when applied to the other large practical feeding system other as reported in [1].

The Tabu Search (TS) algorithm was introduced by Fred Glover in 1986. It is a sequential search process that moves from point to point generally in the direction of the steepest or most decent rise i.e.this research is gradient driven. The TS technique can be considered as adaptive in a sense that it is able to escape local optimums while also maintaining research diversity through the use of short-term and long-term memories. It is, however, obvious that the maintenance of a short-term Tabu list implies the condition for the constant updating displacement resulting from Tabu movements as the research progresses. As a result, the main search parameters of Tabu relate to size and features last Tabu enumerate and in reality the proper setting of such parameters will be largely problem dependent, This is a probable heuristic process involving a lot of search iterations. However, more recently, an improved method of TS proposed by W. M. Lin, and others to economic shipping with non-smooth cost functions with appreciable development in the TS algorithm as reported in as reported in [1].

Evolutionary programming (EP) originally designed by Fogel, in 1960, is similar to genetic search algorithms, from a population of candidate solutions. However, the EP relies primarily on the action of a range of mutation types and does not use crossover. In addition, the EP is not bound by the typical binary representations of the GA genome. Therefore considerable calculation time can be saved at EP. The EP algorithm has been successfully applied to solve ELD with non-smooth fuel cost functions by HT Yang et al. At the later stage, many studies have been reported where evolutionary programming techniques have outperformed genetic algorithms. Nevertheless, the various modifications to EP's core techniques have received intensive study to resolve stochastically changing extremely complicated optimization problems. In recent years, tremendous achievements have been gained by increasing the speed of evolutionary programming algorithms. More recently, the performance of evolutionary programs on ELD problems with different modification of mutation settings in basic evolutionary programming has been examined by Nidul Sinha, et al. The research has resulted in a Enhanced Rapid Evolutionary Program (IFEP) which offers superior performance over all other EP techniques, with respect to convergence rate, solution time, minimum cost and likelihood of achieving better solutions as reported in as reported in [1].

In the electrical energy system, there are two important aspects that matter to the general consumer to know. Liability and the cost of supply. It is intended to consider the role of operational planning in achieving a minimum production cost of electrical energy with several constraints. In addition, this task must be resolved in real time and in a highly reliable manner in a competitive condition due to the deregulation of the electrical industry. Currently available evolutionary based methods like SA, TS, GA, EP and PSO are quite capable of finding the overall or near optimal value for highly non- convex ELD problems but unrealistic for the operation. In addition, the quality of the solution depends on the number of iterations in a process of evolution and the improvement in quality of solution by more number of iterations would in turn require more Solution time. Therefore, EP based algorithms cannot be made to a real-time economical charging part but their results can be used as guidelines for optimal operation. In this regard, newer categories of artificial neural networks have proven to be highly efficient and reliable technique for real-time economic expedition operation, if the neural network is trained correctly with the precise training modemsas reported in [1].

Recently, there has been considerable interest in creating hybrid systems, especially between artificial neural networks and global research methods. In these cases, neural networks are formed or configured using global research methods. Real-time application requires in particular fast calculation for result and high reliability rather than high accuracy. An integrated approach using EP based methods and ANN has the potential to meet the real-time performance requirements of the economical shipment of load. In the hybrid technique, the training models for the ANN are produced on off -line by EP-based methods as it is able to search for the optimal overall solution. The formation of the ANN is off-line in which ANN accumulates knowledge of the given input - product of the data pairs. Once, the network is fully formed, online mining would involve only a chain of simple arithmetic operations that can be completed in a very short period of time. Thus, globally qualified ANN can be considered as an analytical alternative to EP based methods and many interesting applications of the hybrid technique in the field of feeding system have been reported in the literature as reported in [1].

II. Introduction to Economic Dispatching

The economic dispatching is an optimization problem which consists in distributing the production of the requested active power between the various power stations of the network, so as to exploit it in the most economical way possible. This distribution must obviously respect the production limits of the plants. The objective function to be optimized is therefore the cost of production [2].

The problem of lossless economic dispatching is complex because the only parameter that influences the cost is the active power generated by the plant (without taking into account the power lost in the lines during power transits between power plants and loads). The flow of power is another limitation of the economic dispatching which represents the static aspect of the problem. Indeed, when we solve an economic dispatching, we do it for a request at a precise moment. When the problem takes on a dynamic dimension, that is to say when the demand evolves in a given time interval (a day for example), it is then necessary to take into account the states of the power stations as well as the changes of states which cause additional costs. For example, if the demand increases over time, it will probably be necessary to run a plant that was shut down to meet this increased demand, and the cost to start this plant must be taken into account in the future optimization. The treatment of such a problem is called "unit commitment" [2].In this present work we are interested in static economic dispatching.

2.1 Basic Model of Economic Load Dispatch

A. Objective Function

The highest cost of the generation is the cost of fuel, other expenses include such as work, maintenance, safety, stability and aesthetics, and these are economic factors. The cost of production of a power plant is usually modeled by a polynomial function of the second degree as a function of the power generated. In this case, the objective function, which represents the total production cost of all generation units, is expressed as [3]:

$$Ct = \Sigma ngCi = \Sigma ng\ (\alpha i + \beta iPimin + \gamma iP2) \quad (1)$$

$$C = \alpha + \beta P + \gamma P2 \quad (2)$$

Where, C_i = The cost function of the plant (i) express in unit/ h.

α_i = The basic cost coefficient of the generator (i).

β_i = The linear cost coefficient of the generator (i).

γ_i = The quadratic cost coefficient of the generator (i).

P_i = The active power generated by the central unit (i).

ng = Number of generators linked to the network.

C_t = The total cost of production.

In a first place we will consider that the cost curve (the evolution of the cost compared to the power generated) has a parabolic shape as shown in Figure 1

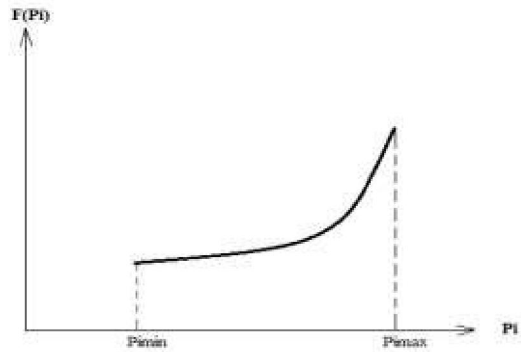

Figure 1: The variation of the cost according to the power generated

III. Objective of Research Work

The basic objective of an economical dispatching is the generation and the exploitation at minimal cost of the electrical energy satisfying all the demand with all the constraints of system. According to the bibliographical summary, we found that several classical and modern methods have been used to solve the problem of economic dispatching of electrical energy. Currently there is a new approach which is the application of artificial intelligence, among which we find the following algorithms:

Particle Swarm Optimization (PSO)

So, the purpose of this work is to use the above mentioned methods for solving the economic load dispatch problem of electrical energy.

3.1 Particle Swarm Optimization

According to Particle Swarm Optimization (PSO) was developed by James Kennedy and Russell Eberhart in 1995 where the concept of non-linear function optimization is introduced with the purpose of understanding social behaviors. In 1998, Russel and Shi modify the optimization process by adding the inertia weight that balances the global and local search of the particles. [6]. The main goal of this work is to perform the optimization of the cost of the combustible in a 30-node IEEE system with distributed generation subject to voltage and power restrictions in each one of the nodes using PSO. According to [2], the equations and restrictions that must be satisfied to develop the problem are: Total combustible cost function:

$$f(P_G) = \sum_{i=1}^{N_g} f_i(P_{Gi})$$

Active power with the quadratic cost function:

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i$$

The quadratic cost function has three coefficients, a, b and c where a represents all the costs in terms of efficiency, b represents the costs that are proportional to the generated power and c represents the costs that are present even when there is no generation. The restrictions that must be satisfied are the following: The power generated must be the same than the demanded power plus losses.

$$\sum_{i=1}^{N_g} P_{Gi} = P_{Demanded} + P_{Losses}$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}$$

Generator	A	B	C	Pmin	Pmax
1	0.00375	2.0	0	50	200
2	0.175	1.75	0	20	80
5	0.0625	1.00	0	15	50
8	0.0083	3.25	0	10	35
11	0.0250	3	0	10	30
13	0.0250	3	0	12	40
23	0.0020	1.40	0	1	3.2
24	0.0020	1.40	0	1	8.7
26	0.0020	1.40	0	1	3.5
29	0.0020	1.40	0	1	2.4
30	0.0020	1.40	0	1	10.6

Table 1: Coefficients and Power For Ieee 30-Node System

3.2 Operation of PSO

PSO consists of a fixed amount of particles that move in a determined search space, with a certain position and velocity, where each one of these particles is a possible solution. The optimization is performed in terms of the objective function where each particle knows its best position obtained during the process and is called the Personal Best (Pbest); in the same way, the other particles know what is the best position obtained by the group and is called the Global Best (Gbest) [8]. These values are used to calculate the new velocity values of the particles in the next iteration. The equations for the calculation of the velocity and position are

$$v_i(k+1) = v_i(k) + g_{1i}(p_i - x_i(k)) + g_{2i}(G - x_i(k))$$

$$x_i(k+1) = x_i(k) + v_i(k+1)$$

Where i is the particle number, k is the discrete time index, v is the velocity of the i-th particle, x is the position of the i-th particle, p is the best position found on the i-th particle and G the best position found by the swarm. Additionally, those equations have random numbers in the [0, 1] interval applied to the i-th particle.

Each particle changes position from the current one to the next one by modifying its velocity through the position equation until the number of desired iterations is reached. To perform the PSO, the MATLAB software is used taking as a basis the Particle Swarm Optimization Toolbox [9]. It was developed by Brian Birge in 2005 and received an update in 2006. Although it has not been updated in ten years, it remains a reference point in several works and investigation tools.

3.3 Use of Pso To Optimize The Economic Dispatch In The Ieee 30-Node System With Distributed Generation Sources

Five generators were added in the nodes indicated on fig. 2 and their characteristics are detailed in Table 4. These new generators, present in the system, will always be delivering the total of their available generation since it is needed that their total capacity is considered when performing the optimization of the economic dispatch. With the purpose of maintaining the alternative generators on full load, the values of the coefficients a, b and c were adjusted in such manner that, when performing the optimization process, the algorithm guaranteed that these generators where dispatching at 100% of their capacity. This lead the dispatch of conventional generators to adjust to that condition and the values added to the initial IEEE 30-node system values. The coefficients used for the systems are shown in

NODE	GA OFF	RGA	EP	GA FUZZY	GA MGA	PSO
PG1	175.64	174.0	173.84	178.17	183.75	173.28
PG2	48.94	46.80	49.99	45.16	46.77	48.03
PG5	21.17	22.00	21.38	20.65	21.23	21.31
PG8	22.64	23.90	22.63	21.29	15.72	24.47

PG11	12.43	11	12.92	15.16	10.71	12.35
PG13	12.00	14.50	12.00	12	14.40	12
Cost	802.30	804.0	802.62	8001.21	800.48	798.34
Losses	9.43	8.84	9.39	9.03	9.22	8.06

Table 2: Data Obtained By Different Authors In A Ieee 30-Node System (Ga Opf, Rga, Ep, Ga Fuzzy, Ga- Mga) Vs Pso.

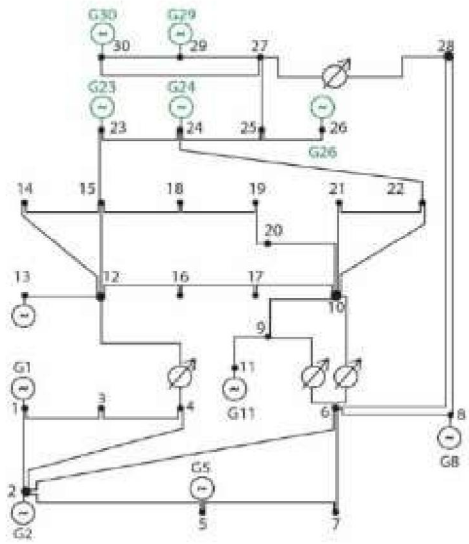

Figure 2: Modified Ieee 30-Node System.

IV. Performance Analysis

An economic load dispatch is performed on a bus system with six generator using Ant Lion Optimization and Particle Swarm Optimization. The optimization is performed in terms of the objective function where each particle knows its best position obtained during the process and is called the Personal Best (Pbest); in the same way, the other particles know what is the best position obtained by the group and is called the Global Best (Gbest) shown in fig. PSO. These values are used to calculate the new velocity values of the particles in the next iteration. It is observed that Generator 1 is the biggest one of the system and presents a 18.89% power reduction using PSO While ALO gives 16.55%reduction.The total cost of generation is reduced by 2.66% in PSO as compared to ALO.

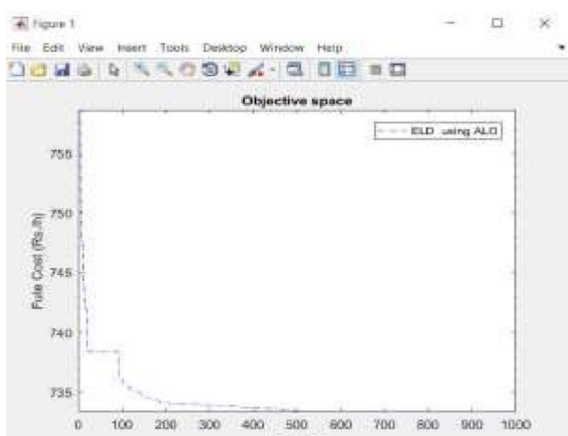

Figure 3: ALO of Fuel Cost Vs Iteration

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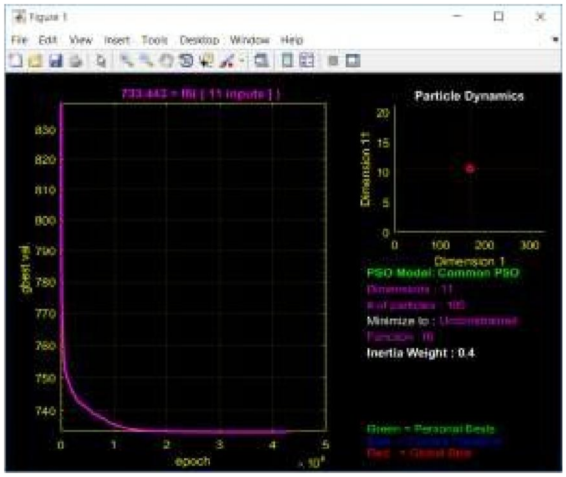

Figure 4: Personal Best (pbest) Global Best(Gbest) shown in PSO.

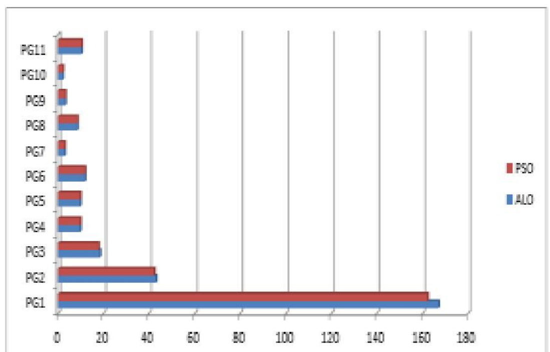

Figure 5: PSO as compared to ALO.

V. Conclusion

A distributed generation cannot always be at full load due to its random nature. PSO has turned out to be effective in comparison to the results obtained for the genetic algorithms in terms of the total generation cost and the system losses. The coefficients associated with the cost can be increased to resemble more to real operating conditions, with the purpose of having a more precise calculation in the prices. The inclusion of distributed generation in the system brings a considerable reduction in the generation and, therefore, in the cost of conventional generators. The results obtained for this study are related to distributed generation in general but the modeling could be performed for the different distributed generations that could enter the system for a more specific calculation.

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