Particle Swarm Optimization of Economic Dispatch Problem: A Brief Review Transfer

Elahe Faghihnia[1], Sadegh Khaleghi [2], Reihane Kardehi Moghaddam[2] and Mahdi Zarif[2]
[1]Young Researchers and Elite Club, Mashhad Branch, Islamic Azad University, Mashhad, Iran
[2]Department of Electrical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran

Keywords: Economic Dispatch, Optimization, Particle Swarm Optimization.

Abstract: Electrical energy production has changed various features of the energy manufacturing. According to this map, lack of energy supplies, improving energy cost, environment matter, require optimal economic dispatch. Economic load dispatch (ED) problem is essentially nonlinear. Since we know that the traditional methods donot have the ability to solve problems like this for reasons such as caught up in the trap of local optimal point or low convergence speed. Therefore, the use of algorithms that are more powerful is inevitable. An efficient algorithm for solving ED problem is particle swarm optimization considering to its fast convergence to global optima and computationally efficiency. PSO based algorithms has achieved a pluperfect identification of the best solution for such kind of EDPs in last decade. In this paper, we try various techniques associated with PSO, fully checked.

1 INTRODUCTION

Today's world, a world in which economic life is importantو ED problem Plays a very important role in the development and updated Modes of production and consumption and optimize them for an efficient and economical network in all areas of production, distribution and transmission in a power systems. The main purpose of ED is to be planed as a Coordinator system which has efficient and responsive flawless generating parts in order to meet the load demand while Maintain the balance between supply and demand .

In addition it should achieve the lowest cost and satisfies all the constraints of the network. To achieve this aim, we should have a detailed study on the optimization methods to obtain an optimal algorithm which has powerful network with high reliability basically, ED problem was definite as economic cost dispatch(ECD), though due to the transformation of clean air act in 1990s, survival of emission dispatch (EMD) leads to the formulation of mixed emission economic dispatch (CEED) and emission controlled economic dispatch (ECED) problem formulation, as individual optimization of these two contradictory objective will not serve the idea. Numerous traditional methods like Bundle method (Mezger and de Almeida, 2007), nonlinear programming (Mariano et al., 2007), (Martinez Ramos et al.,2001), mixed integer linear programming (Martinez Ramos et al., 2001),(G. W. Chang et al., 2001),(Garcia-Gonzalez and Castro, 2001), (García-González et al., 2007), dynamic programming (S.-C. Chang et al.,1990), quadratic programming (Finardi et al., 2005), Lagrange relaxation method (Shiina and Watanabe, 2004), network flow method (Franco et al., 1994), direct search method (Wood and Wollenberg, 2012) reported in the literature are used to solve such problems.

Practically, ED problem is nonlinear, nonconvex type with multiple local optimal point due to the liability of valve point loading effect, multiple fuel options with diverse equality and inequality constraints. Conventional methods have unsuccessful to solve such problems as they are sensitive to major approximations and converge into local optimal point and computational convolution. Modern exploratory optimization methods recommended by researchers based on utilizable studies and artificial intelligence theories such as evolutionary programming (Fogel and Fogel, 1996), genetic algorithm (Whitley, 1994), simulated annealing (Hwang, 1988), ant colony optimization (Blum, 2005), Tabu search (Moscato, 1993), neural network (Dayhoff, 1990), particle swarm optimization (Kennedy, 2010), Sure solution introduced. Every method has its benefits and trouble. Although PSO has attained reputation as the finest

Faghihnia E., Khaleghi S., Moghaddam R. and Zarif M..
Particle Swarm Optimization of Economic Dispatch Problem: A Brief Review Transfer.
DOI: 10.5220/0005507400720077
In *Proceedings of the 12th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2015), pages 72-77
ISBN: 978-989-758-122-9

solution algorithm for such problems. This article is a response entry on previous activity of importance of Population-based approaches such as PSO algorithm to solve the numerous ED problems.

This paper is arranged as follows: Section 2 describes the cost function of ED problem with the associated constraints of it. Section 3 provides a comprehensive overview of the methods that have been done so far. All methods are compared in the table, in terms of mean time to achieve the best result in the ED problem, in sections 4. In section 5 finally, the results are concluded.

2 AN INTRODUCTION TO EDP PROBLEM

The most important thing that should be noted in EDPs for generating the electricity is to set of generators such that the equilibrium is established between supply and demand and finally the Minimum Cost Reduction, considering all the constraints, happened. Along with all these words, it should not be forgotten that in order to achieve the desired, using a procedure is necessary to achieve optimal point. In a practical matter, Valve-Point loading effect also must be considered which will complicate the issue, more than before because virtually a linear section will be added to the original problem and when it becomes a big problem that it wants to be solved by the methods listed in the previous. So there is no alternative unless the use of new optimization techniques.

This methods achieve to a local or global optimization point without considering the nature of object function. Hence, to reach desirable results it is important to use modern methods like evolutionary optimization algorithms. As mentioned earlier, one of the disadvantages of the traditional optimization methods is being trapped in a local optimum solution. Although these methods are useful in identification of linear systems, but due to the properties of nonlinear systems and the existence of multiple local optimal point, these methods are usually not effective in detecting nonlinear systems. The problem of parameter estimation of nonlinear systems can be easily changed to an optimization problem that can be solved by intelligent methods.

3 FORMULARIES ED PROBLEM

The cost function of the economic dispatch problem is proposed to minimize the fuel cost of thermal power plants for a given load demand when involved to various constraints.

The overall cost function of the EDP is defined as follows:

$$\mathrm{Min}_f = \sum_{j=1}^{n} F_j\left(P_j\right) \tag{1}$$

Where n is the total number of generator units and $F_j(P_j)$ is a unit fuel cost in terms of $^{\$}/_{h}$.

The objective function regardless of valve-point loading effect is expressed as follows:

$$\mathrm{Min}_f = \sum_{j=1}^{n} F_j\left(P_j\right) = \sum_{j=1}^{n}(a_j + b_j P_j + c_j P_j^2) \tag{2}$$

Where P_j is the power generated per MW by j^{th} unit. The coefficients a_j, b_j and c_j are the unit cost of j^{th} production. Considering the valve-point loading effect, the objective function is defined as follows:

$$\mathrm{Min}_f = \sum_{j=1}^{n} F_j\left(P_j\right) = \sum_{j=1}^{n}[a_j + b_j P_j + c_j P_j^2 + \left|e_j \sin(f_j(P_j^{min} - P_j))\right|] \tag{3}$$

Where e_j and f_j are constant coefficients which are related to the valve-point loading effects that these coefficients are limited by the following constraints:

$$\sum_{j=1}^{n} P_j = P_D \tag{4}$$

$$P_j^{min} \le P_j \le P_j^{max} \tag{5}$$

P_D is the total power demand in MW. P_j^{min} and P_j^{max}, respectively, are defined as the minimum and maximum of j^{th} units.

4 TRADITIONAL PSO

PSO is a social search algorithm that has been modeled based on the social behavior of the flocks of birds, fishes and warming theory in particular. In PSO algorithm, at the first, particles distribute uniformly in the search space and create the population, than in the second stage particles change their states in the search space according to their own experience and knowledge and also the knowledge of their neighbors. So particles learn from each other and searching process of each particle is affected by the state of other particles. Indeed PSO algorithm is based on the principle that each particle sets its state in the search space, with respect to the best state in its locality and best state of other agents (particles).

Each particle in PSO includes three d-dimensional vectors where d is the dimension of the search space for i-th particle. These three factors include current position of i-th partial (x^i), The velocity for i-th particle(v^i), And the best position that ever has experienced by i-th particle(x^{ibest}). x^i is a set of coordinates that demonstrates current space of i-th particle. In each iteration of algorithm, x^i calculates as a solution of problem. If this position for x^i is better than the previous answers, it would save in x^{ibest}. f^i is the objective function value, obtained from x^i and (f^{ibest}) represents the objective function value, obtained from x^{ibest}. Saving f^{ibest} is a necessary process for doing the next comparison, but saving f^i is not required. In each iteration new values for x^i and v^i, Are achieved and velocity and position of each particle will be updated.

In fact, for the swarm particles, solving the problem is a social concept which is achieved from behavior of each particle and from the interaction between them. Best situation that is found with all particles is represented as x^{gbest}, and is chosen by comparison of all values of f^{ibest} for all particles and between all x^{ibest}. Objective function value at x^{gbest} represented as f^{ibest}. n is the number of particles and these concepts can be mathematically states as:

$$x^{ibest}[t] = \mathrm{argmin} f(x^i[\zeta]) = \mathrm{argmin}_{\zeta \geq t}\{f(x^i[t]), f(x^{ibest}[t-1])\} \tag{6}$$

$$f^{ibest}[t] = f(x^{ibest}[t]) = min_{\zeta \leq t} f^i[\zeta] = min\{f^i[t], f(f^{ibest}[t-1])\} \tag{7}$$

$$f^{ibest}[t] = f(x^{ibest}[t]) = min_{\zeta \leq t} f^i[\zeta] = min\{f^i[t], f(f^{ibest}[t-1])\} \tag{8}$$

$$f^{gbest}[t] = f(x^{gbest}[t]) = min_{i=1,,\dots,n} f^{ibest}[t] \tag{9}$$

Relationships that change speed and position of particles are as follows:

$$V_j^i[t+1] = WV_j^i[t] + c_1 r_1\left(X_j^{ibest}[t] - X_j^i[t]\right) + c_2 r_2\left(X_j^{gbest}[t] - X_j^i[t]\right) \tag{10}$$

$$X_j^i[t+1] = X_j^i[t] + V_j^i[t+1] \tag{11}$$

5 A BRIEF REVIEW

Traditional PSO algorithms because of the simplicity and because in the first it was a relatively high accuracy algorithm, It was considered as a powerful algorithm. As previously noted, in this algorithm, the particles are updated at every stage of their replication in order to speed to the position of the particle that is allocated the best results until this iteration and to the best of his own experience. The algorithm is defined as each particle alone is capable after passing the problem constraints, considered as an answer and at all stages of their repeated attempts to bring the desired response and for the ED problem, particles has all the characteristics of production and its constraints.

One of the fundamental problems in intelligent algorithms is being trapped in a local optimum solution that makes a drastic reduction in the rate of convergence, and accuracy of the algorithm. To resolve this problem different algorithm with a change in the coefficient of inertia attempted to improve system performance. Experimental studies show that relatively large inertia weight has the ability to search for more. While weight reduction with a coefficient of inertia, leads to the speedy convergence of the algorithm. Therefore, the weight of inertia as a linear or nonlinear function should be reduced.

Various methods have been tried with different methods to improve the traditional algorithm. Some changes were applied to the algorithm itself. This means that it can be said as new methods and for other algorithm only changes in weight matrices have applied.

For example (Meng, Wang, Dong, & Wong, 2010) is examined various amounts of Weight matrix (W) and best values for traditional PSO have been proposed. In (Park, Jeong, Shin, & Lee, 2010) an appropriate weight factor suggested for solving non-convex ED problems in this article also THE simulation results from weight matrix of IPSO have been compared with the traditional weight matrix. The proposed IPSO algorithms have been successfully applied to three different systems and it was proven that it does not get stuck in the trap of local optimality. In 2003 a useful article was published (Victoire & Jeyakumar, 2004)and it was introduced as a method of optimization and showed that on the basis of the results of experiments and simulations have been conducted it is better, in terms of solving the optimization problem convergence rate, solution time, minimum cost, and chance of achieving better solutions until that time.

Until 2004, Sequential quadratic programming (SQP), seemed to be the best method to solve the problems for nonlinear constrained optimization. In terms of efficiency, correctness, and percentage of satisfied answer, after conducting several experiments on benchmark functions. The method follows nearly to Newton's formula for constrained optimization just as is resolved as other optimization problems. At each iteration using the method an initial estimate is made based on the Hessian of the Lagrangian function using a BFGS quasi-Newton updating method. After that, the main method used for generate a quadratic programming (QP). The code for this program can be summarized in the following steps:

Step1: Getting information from the user or system

Step2: Generate random points in the search space and make the initial velocity for particles of PSO

Step3: Update the value of each particles in the optimization problem and inertia weight and count t.

Step4: Determine the best particle among all the particles of the moment called global best particle and its cost.

Step5: Choose best particle as agent to start the SQP method to solve the ED problem otherwise go to the step7.

Step6: If the particles created in the SQP method was more efficient than PSO method, replace the two particles together.

Step7: Modify the particles in the search space and its velocity.

Step8: Check out the exit condition.

(As an example for exit condition can be when there is no betterment in the iteration.)

In 2010, a new method was introduced in the field of intelligent optimization called QPSO (Meng et al., 2010). The advantage in this method was presented as it can have a higher convergence rate and enhance the search space. The success of the method was tested on 5 benchmark function and proved its efficiency practically. In the QPSO, the state of each particle and its velocity is introduced by quantum bit and an angel.

One of the fundamental problems in intelligent algorithms is being trapped in a local optimum solution that makes a drastic reduction in the rate of convergence, and accuracy of the algorithm. To resolve this problem different algorithm with a change in the coefficient of inertia attempted to improve system performance. Experimental studies show that relatively large inertia weight has the ability to search for more. While weight reduction with a coefficient of inertia, leads to the speedy convergence of the algorithm. Therefore, the weight of inertia as a linear or nonlinear function should be reduced.

As the process of searching for a PSO algorithm is very complex and nonlinear, decreasing inertia weight and acceleration coefficients without getting feedback from the global optimal fitness does not properly reflect the actual search process. In fact, if general fitness is great, the particles are far from ideal point. Hence, high speed is required to globally search the solution space that means [w, c1, c2] should have greater quantities. Against, when only small movements are necessary the coefficients must be adjusted in small quantities. According to this fact, the proposed inertia weight and acceleration coefficients are adjusted as a function of the overall best fit. Hence, Inertia weight and acceleration coefficients are proposed as follows:

$$w = 1/\left(1 + \exp\left(-\alpha \times F(G_t)\right)^n\right) \tag{12}$$

$$\mathrm{c_i} = 1 + \frac{1}{1 + \exp\left(-\alpha \times \mathrm{F(G_t)}\right)^{\mathrm{n}}}, i = 1{,}2 \tag{13}$$

Where $F(G_t)$ is the t^{th} iteration of the global optimum fitness n and α parameters need to be pre-defined. α value can be set as follows:

$$\alpha = \frac{1}{\mathrm{F(G_t)}} \tag{14}$$

In this case, coefficients vary according to the degree of improvement in overall fitness. Through the study of non-linear modulation parameter n, set a reasonable choice for this parameter is derived in the (1,2) range. Moreover, under this assumption and the definitions above, one can conclude that:

$$0.5 \le \mathrm{w} < 1, 1.5 \le \mathrm{c_1} < 2, 1.5 \le \mathrm{c_2} < 2 \tag{15}$$

6 RESULTS OF THE FIRST EXPERIMENT

For the first test IPSO algorithm is applied to three generating units and the results obtained with twelve other algorithms. For each system, the best results and the best average results are compared and improvement is clearly evident in the results. It should be noted that the technical specifications of the system used in the experiments are Pentium Duo-Core computer with CPU 2.6 GHz and 4 GB RAM memory And results obtained with MATLAB r2013b. Also, all the data used were extracted from (S.-C. Chang et al., 1990). To perform experiments on three applications mentioned above, the initial population of 40 is considered. Coefficients c1 and c2 are considered as mentioned in the past content.

6.1 The First System under Test

The system consists of three units that the total power of 850 MW generation units of this test is considered. The algorithm runs 50 times and the best result and the average best individual results are listed in Table 1. The experiments were carried out for algorithms, PSO and IPSO and the results were compared with other algorithms in the same conditions.

Fig.1 shows the coefficients for simulation results of 12 methods and Fig.2 shows the system consists of 3 generating units with a load demand of 850MW and the comparison of the best and mean fuel costs of 50 trail runs achieved by using methods with those reported in the paper.

Table 1: The coefficients used in the simulations (G=Generator).

G	P_{min}	P_{max}	a	b	c	e	f
1	100	600	0.001562	7.92	561	300	0.0315
2	50	200	0.004820	7.97	78	150	0.063
3	100	400	0.001940	7.85	310	200	0.042

Table 2: Compare the values of all the methods at three plants.

Algoritms	Best results	Mean results
CEP	8234.07	8235.97
FEP	8234.07	8234.24
MFEP	8234.08	8234.71
IFEP	8234.07	8234.16
EP	8234.07	8234.16
EP-SQP	8234.07	8234.09
PSO-SQP	8234.07	8234.72
Firefly	8234.07	8234.08
SPSO	8234.07	8234.18
QPSO	8234.07	8234.10
PSO	8234.07	8234.21
IPSO	8234.07	8234.38

Table 3: Comparison Of Best Results Between IPSO And PSO.

THE 3-UNIT SYSTEM		
Algorithm	**IPSO**	**PSO**
P1/MW	399.1973	300.2635
P2/MW	126.4041	400.0000
P3/MW	324.3986	149.7364
Total generation/MW	850	850
Cost/($.$h^{-1}$)	8234.067	8234.073
Mean time/s	0.067	0.063

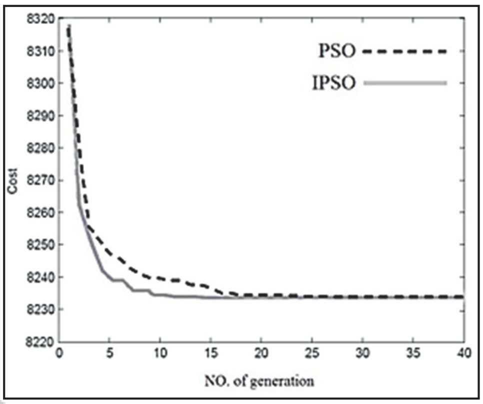

Figure 1: Convergence characteristics of IPSO and PSO for the 3-unit test system.

7 INTERPRETATION OF TABLES AND THE SIMULATION

In table1 the coefficients used for the simulation are presented, and in table 2 traditional PSO method compared with 11 other methods from the perspective of the average number of runtime, the response from the best value of cost function mean time from 50 times perform the program. The results obtained from this comparison are showing the improved method is superior to other methods of best value of cost function vision and from the perspective of time, a slight increase is observed.

Fig.1 depicted the convergence characteristics of the IPSO and PSO for the 3-unit test system. From Fig.1, it can be observed that the convergence rate of IPSO is better than PSO algorithm.

8 RESULTS, ANALYSIS AND CONCLUSIONS

This paper is an overview of the method of constrained optimization and we try to introduce a new index for solving the ED problems with valve point loading effects and tried to introduce methods which were much more effective. Finally method is implemented to reach to a better global minimum and mean point. After numerous tests it can be concluded that the global optimum cost for mean cost function in 3-unit mode decreases while the response time has a little increment and also the global optimum cost for best cost function in 3-unit mode has not any changes.

REFERENCES

Blum, C. (2005). Ant colony optimization: Introduction and recent trends. *Physics of Life Reviews, 2(4)*, 353-373.

Chang, G. W., Aganagic, M., Waight, J. G., Medina, J., Burton, T., Reeves, S., & Christoforidis, M. (2001). Experiences with mixed integer linear programming based approaches on short-term hydro scheduling. Power Systems, IEEE Transactions on, 16(4), 743-749.

Chang, S.-C., Chen, C.-H., Fong, I.-K., & Luh, P. B. (1990). Hydroelectric generation scheduling with an effective differential dynamic programming algorithm. Power Systems, IEEE Transactions on, 5(3), 737-743.

Dayhoff, J. E. (1990). Neural network architectures: an introduction: Van Nostrand Reinhold Co.

Finardi, E. C., Silva, E. L. d., & Sagastizábal, C. (2005). Solving the unit commitment problem of hydropower plants via Lagrangian relaxation and sequential quadratic programming. Computational & applied mathematics, 24(3), 317-342.

Fogel, D. B., & Fogel, L. J. (1996). An introduction to evolutionary programming. Paper presented at the Artificial Evolution.

Franco, P., Carvalho, M., & Soares, S. (1994). A network flow model for short-term hydro-dominated hydrothermal scheduling problems. *Power Systems, IEEE Transactions on, 9(2)*, 1016-1022.

Garcia-Gonzalez, J., & Castro, G. A. (2001). Short-term hydro scheduling with cascaded and head-dependent reservoirs based on mixed-integer linear programming. Paper presented at the Power Tech Proceedings, 2001 IEEE Porto.

García-González, J., Parrilla, E., & Mateo, A. (2007). Risk-averse profit-based optimal scheduling of a hydro-chain in the day-ahead electricity market. *European Journal of Operational Research, 181(3),* 1354-1369.

Hwang, C.-R. (1988). Simulated annealing: theory and applications. Acta Applicandae Mathematicae, 12(1), 108-111.

Kennedy, J. (2010). Particle swarm optimization Encyclopedia of Machine Learning (pp. 760-766): *Springer*.

Mariano, S., Catalao, J., Mendes, V., & Ferreira, L. (2007). Profit-based short-term hydro scheduling considering head-dependent power generation. Paper presented at the Power Tech, 2007 IEEE Lausanne.

Martinez Ramos, J., Lora, A. T., Santos, J. R., & Expósito, A. G. (2001). Short-term hydro-thermal coordination based on interior point nonlinear programming and genetic algorithms. Paper presented at the Power Tech Proceedings, 2001 IEEE Porto.

Meng, K., Wang, H. G., Dong, Z., & Wong, K. P. (2010). Quantum-inspired particle swarm optimization for valve-point economic load dispatch. Power Systems, IEEE Transactions on, 25(1), 215-222.

Mezger, A. J., & de Almeida, K. C. (2007). Short term hydrothermal scheduling with bilateral transactions via bundle method. *International Journal of Electrical Power & Energy Systems, 29(5),* 387-396.

Moscato, P. (1993). An introduction to population approaches for optimization and hierarchical objective functions: *A discussion on the role of tabu search. Annals of Operations Research, 41(2),* 85-121.

Park, J.-B., Jeong, Y.-W., Shin, J.-R., & Lee, K. Y. (2010). An improved particle swarm optimization for nonconvex economic dispatch problems. Power Systems, IEEE Transactions on, 25(1), 156-166.

Shiina, T., & Watanabe, I. (2004). Lagrangian relaxation method for price-based unit commitment problem. Engineering Optimization, 36(6), 705-719.

Victoire, T. A. A., & Jeyakumar, A. E. (2004). Hybrid PSO–SQP for economic dispatch with valve-point effect. Electric Power Systems Research, 71(1), 51-59.

Whitley, D. (1994). A genetic algorithm tutorial. Statistics and Computing, 4(2), 65-85.

Wood, A. J., & Wollenberg, B. F. (2012). Power generation, operation, and control: John Wiley & Sons.