Economic Load Dispatch Using Improved Harmony Search

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Abstract: - This paper presents the use of the improved harmony search method for solving economic load dispatch problems. The harmony search method mimics a jazz improvisation process by musicians in order to seek a fantastic state of harmony. To assess the searching performance of the proposed method, a six-unit thermal generating system acquired from the standard IEEE 30-bus test system was challenged. Satisfactory results obtained from the proposed method were compared to those obtained by genetic algorithms, evolutionary programming, adaptive tabu search and particle swarm. Also, effects of valve-point loading units were included and discussed.

Key-Words: - Economic dispatch, genetic algorithms, evolutionary programming, adaptive tabu search, particle swarm optimization

1 Introduction

Engineering optimization problems contain many practical complex constraints. They can be formulated and therefore solved as nonlinear programming models. The methods for solving this kind of problems include traditional mathematical programming (such as linear programming, quadratic programming, dynamic programming, gradient methods and Lagrangian relaxation approaches [1]) and modern meta-heuristic methods (such as simulated annealing, genetic algorithms, evolutionary algorithms, adaptive tabu search, particle swarm optimization, etc [2]). Some of these methods are successful in locating the optimal solution, but they are usually slow in convergence and require very expensive computational cost. Some other methods may risk being trapped to a local optimum, which is the problem of premature convergence.

Economic load dispatch is one of well-known problems in a field of power system optimization [3]. The problem of dividing the total load demand among available online generators economically and also satisfying various system constraints simultaneously is called economic load dispatch. This is an important task in power system for allocating power generations among the committed units such that the constraints imposed are satisfied, the energy demands are met, and the corresponding cost is minimized. Improvements in scheduling of the unit generations can lead to significant cost savings. In view of the nonlinear characteristics of this problem, there is a demand for the optimization methods that do not have restrictions on the shape of the fuel-cost curves [4]. As some stochastic search algorithms as mentioned above may prove to be very effective in nonlinear economic load dispatch problems due to having no restrictions on the shape of the cost curves. Although it does not guarantee the globally optimal solution in limited time, it does normally provide good solutions with computational cost [5].

In the past decades, many optimization algorithms are tried with different kinds of constraints. Several mathematical programming and modern heuristic search can be found extensively [5,6]. Evolutionary search methods have becomes more popular to solve any mathematical functions [7]. The natural selection and meta-heuristic methods are useful for finding the global optimum solution, since they all are maintaining population of solutions to the considered problem. Harmony search method has been developed by Geem et al [8]. It imitates the improvisation process of musicians to find the perfect state of harmony. It has been successfully applied to various mathematical optimization problems in the application field of civil and mechanical engineering. However, its first version was invented as a combinatorial optimization where decision variables are discrete. To apply the harmony search method to the real world engineering in which many search spaces are continuous, some procedure of the harmony search method must be modified to be able to handle continuous search variables. Hence, it is an improved version of the harmony search method which is called as the improved harmony search method.

This paper solves an economic load dispatch problem using the improved harmony search method. The test considers a six-unit generating system acquired from the standard IEEE 30-bus test system [9]. The results obtained by the improved harmony search method are compared with those of other promising methods. The proposed method proves to be a robust optimization technique for solving economic load dispatch problems.

This paper organizes a total of five sections. Next section, Section 2 illustrates economic load dispatch problems with corresponding mathematical expressions of its objective and various practical constraints. Section 3 gives the brief of some meta-heuristic search methods used for comparative purpose. It also provides the algorithm procedure, described step-by-step. Section 4 is the simulation results and discussion. Conclusion remark is in Section 5.

2 Problem Formulation

Almost all coal, nuclear, geothermal, solar thermal electric, and waste incineration plants, as well as many natural gas power plants are thermal. Natural gas is frequently combusted in gas turbines as well as boilers. The waste heat from a gas turbine can be used to raise steam, in a combined cycle plant that improves overall efficiency. Power plants burning coal, oil, or natural gas are often referred to collectively as fossil-fuel power plants. Some biomass-fueled thermal power plants have appeared also. Non-nuclear thermal power plants, particularly fossil-fueled plants, which do not use cogeneration are sometimes referred to as conventional power plants. Commercial electric utility power stations are most usually constructed on a very large scale and designed for continuous operation. Electric power plants typically use three-phase or individual-phase electrical generators to produce alternating current (AC) electric power at a frequency of 50 Hz or 60 Hz (hertz, which is an AC sine wave per second) depending on its location in the world. Other large companies or institutions may have their own usually smaller power plants to supply heating or electricity to their facilities, especially if heat or steam is created anyway for other purposes. Shipboard steam-driven power plants have been used in various large ships in the past, but these days are used most often in large naval ships. Such shipboard power plants are general lower power capacity than full-size electric company plants, but otherwise have many similarities except that typically the main steam turbines mechanically turn the propulsion propellers, either through reduction gears or directly by the same shaft. The steam power plants in such ships also provide steam to separate smaller turbines driving electric generators to supply electricity in the ship. Shipboard steam power plants can be either conventional or nuclear; the shipboard nuclear plants are mostly in the navy. There have been perhaps about a dozen turbo-electric ships in which a steam-driven turbine drives an electric generator which powers an electric motor for propulsion. In some industrial, large institutional facilities, or other populated areas, there are combined heat and power (CHP) plants, often called cogeneration plants, which produce both power and heat for facility or district heating or industrial applications. AC electrical power can be stepped up to very high voltages for long distance transmission with minimal loss of power. Steam and hot water lose energy when piped over substantial distance, so carrying heat energy by steam or hot water is often only worthwhile within a local area or facility, such as steam distribution for a ship or industrial facility or hot water distribution in a local municipality.

Power is energy per unit time. The power output or capacity of an electric plant can be expressed in units of megawatts electric (MWe). The electric efficiency of a conventional thermal power station, considered as saleable energy (in MWe) produced at the plant busbars as a percent of the heating value of the fuel consumed, is typically 33% to 48% efficient. This efficiency is limited as all heat engines are governed by the laws of thermodynamics (See: Carnot cycle). The rest of the energy must leave the plant in the form of heat. This waste heat can go through a condenser and be disposed of with cooling water or in cooling towers. If the waste heat is instead utilized for district heating, it is called cogeneration. An important class of thermal power station is associated with desalination facilities; these are typically found in desert countries with large supplies of natural gas and in these plants, freshwater production and electricity are equally important co-products. Since the efficiency of the plant is fundamentally limited by the ratio of the absolute temperatures of the steam at turbine input and output, efficiency improvements require use of higher temperature, and therefore higher pressure, steam. Historically, other working fluids such as mercury have been experimentally used in a mercury vapour turbine power plant, since these can attain higher temperatures than water at lower working pressures. However, the obvious hazards of toxicity, and poor heat transfer properties, have ruled out mercury as a working fluid.

Real power generation can be allocated to available generating units in many different ways [6]. In this paper, the economic objective and some practical constraints of the economic load dispatch problems are illustrated as follows.

2.1 Economic objective function

The economic dispatch problem is to find the optimal combination of power generation in such a way that the total production cost of the entire system is minimized while satisfying the total power demand and some key power system constraints. The fuel cost for each power generation unit is defined. Hence, the total production cost function of economic dispatch problem is defined as the total sum of the fuel costs of all generating plant units as described follows.

$$F_T = \sum_{i=1}^{N_G} \left\{ a_i P_i^2 + b_i P_i + c_i + \left| d_i \sin e_i \left(P_i^{\min} - P_i \right) \right| \right\} \quad (1)$$

Where

N_G is the total number of generating units
F_T is the total production cost
P_i is the power output of generating unit *i*
$P_i^{\min}$ is the minimum output of generating unit *i*
a_i, b_i, c_i, d_i, e_i are fuel cost coefficients of unit *i*

It should note that (1) describes the fuel cost function in which valve-point loading effect [4,10] is included.

2.2 Problem constraints

There are equality and inequality constraints in this kind of problems. A power balance equation (2) is set as an equality constraint whereas the limits of power generation output (3) are inequality constraints.

$$P_D + P_{Loss} - \sum_{i=1}^{N_G} P_i = 0 \quad (2)$$

$$P_i^{\min} \le P_i \le P_i^{\max},\ i = 1, 2, \cdots, N_G \quad (3)$$

Where

P_D is the total power demand of the plant
P_{Loss} is the total power losses of the plant
$P_i^{\min}$ is the minimum output of generating unit *i*
$P_i^{\max}$ is the maximum output of generating unit *i*

2.2 Economic load dispatch problem

The solution of economic dispatch problem will give the amount of active power to be generated by different units at the minimum production cost for a particular demand while keep operating the system within all the constraint limits. This is the economic load dispatch problems being as a constrained nonlinear optimization problem [3,5,6] as follows.

$$\begin{aligned} &\textit{Minimize} && F_T \\ &\textit{Subject to} && g_i(x) = 0, \forall i \\ & && h_j(x) \le 0, \forall j \end{aligned} \quad (4)$$

Where

x is a vector of decision variables
$g_i(x)$ is an equality constraint *i*
$h_j(x)$ is an inequality constraint *I*

To solve this constrained optimization with some efficient mathematical programming and modern meta-heuristic methods [1,5], penalty method is used to convert a constrained optimization problem to an unconstrained optimization problem. Therefore, problems of a single objective function are formulated and can be solved accordingly. The penalty function can be expressed as follows.

$$P(x) = F_T + \rho \left(\sum_i g_i^2(x) + \sum_j \left[\max\{h_j(x), 0\} \right]^2 \right) \quad (5)$$

Where

ρ is the penalty factor

3 Meta-Heuristic Methods for Solving Optimization Problems

3.1 Genetic algorithms (GAs)

There exist many different approaches to adjust the motor parameters. The GAs is well-known [11-16], there exist a hundred of works employing the GAs technique to identify system parameters in various forms. The GAs is a stochastic search technique that leads a set of population in solution space evolved using the principles of genetic evolution and natural selection, called genetic operators e.g. crossover, mutation, etc. With successive updating new generation, a set of updated solutions gradually converges to the real solution. Because the GAs is very popular and widely used in most research areas where an intelligent search technique is applied, it can be summarized briefly as shown in the flowchart of Fig. 1 [14].

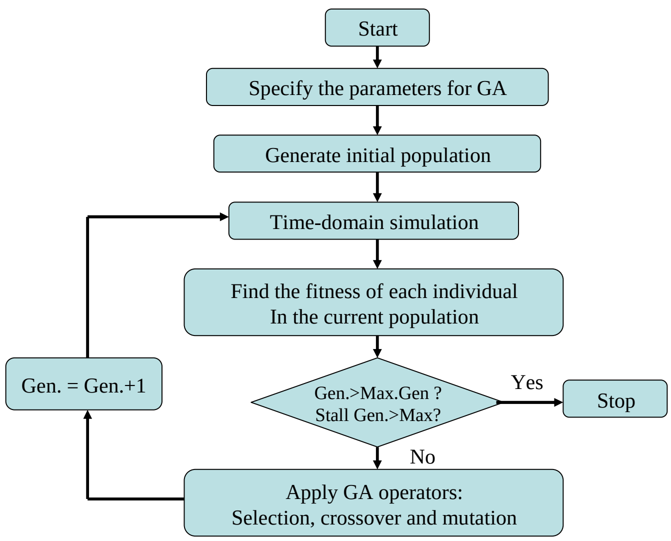

Fig. 1. Flowchart of the GAs procedure

In this paper, the GAs is selected to build up an algorithm to solve economic dispatch problems (all generation from available generating units). To reduce programming complication, the Genetic Algorithms (GADS TOOLBOX in MATLAB [12]) is employed to generate a set of initial random parameters. With the searching process, the parameters are adjusted to give the best result.

3.2 Evolutionary programming (EP)

Evolutionary programming was invented by Lawrence J. Fogel [7] in 1960. At the time, artificial intelligence was limited to two main avenues of investigation: modeling the human brain or neural networks, and modeling the problem solving behavior of human experts or heuristic programming. Both focused on emulating humans as the most advanced intelligent organism produced by evolution. The alternative, envisioned by Fogel, was to refrain from modeling the end product of evolution but rather to model the process of evolution itself as a vehicle for producing intelligent behavior. Fogel viewed intelligence as a composite ability to make predictions in an environment coupled with the translation of each prediction into a suitable response in light of a given goal (e.g. to maximize a payoff function). Thus, the viewed prediction is a prerequisite for intelligent behavior. The modeling of evolution as an optimization process was a consequence of Fogel's expertise in the emerging fields of biotechnology (at the time defined as the utilization of mathematics to describe the functioning of a human operator), cybernetics, and engineering.

Fogel crafted a series of experiments in which finite state machines represented individual organisms in a population of problem solvers. These graphical models are used to describe the behavior or computer software and hardware, which is why he termed his approach "Evolutionary Programming". The experimental procedure was as follows. A population of finite state machine is exposed to the environment – that is, the sequence of symbols that has been observed up to the current time. For each parent machine, as each input symbol is presented to the machine, the corresponding output symbol is compared with the next input symbol. The worth of this prediction is then measured with respect to the payoff function (e.g., all-none, squared error). After the last prediction is made, a function of the payoff for the sequence of symbols (e.g., average payoff per symbol) indicates the fitness of the machine or program. Offspring machines are created by randomly mutating the parents and are scored in a similar manner. Those machines that provide the greatest payoff are retained to become parents of the next generation, and the process iterates. When new symbols are to be predicted, the best available machine serves as the basis for making such a prediction and the new observation is added to the available database. Fogel described this process as "evolutionary programming" in contrast to "heuristic programming" [17-20]. This can be summarized briefly as shown in the flowchart of Fig. 2.

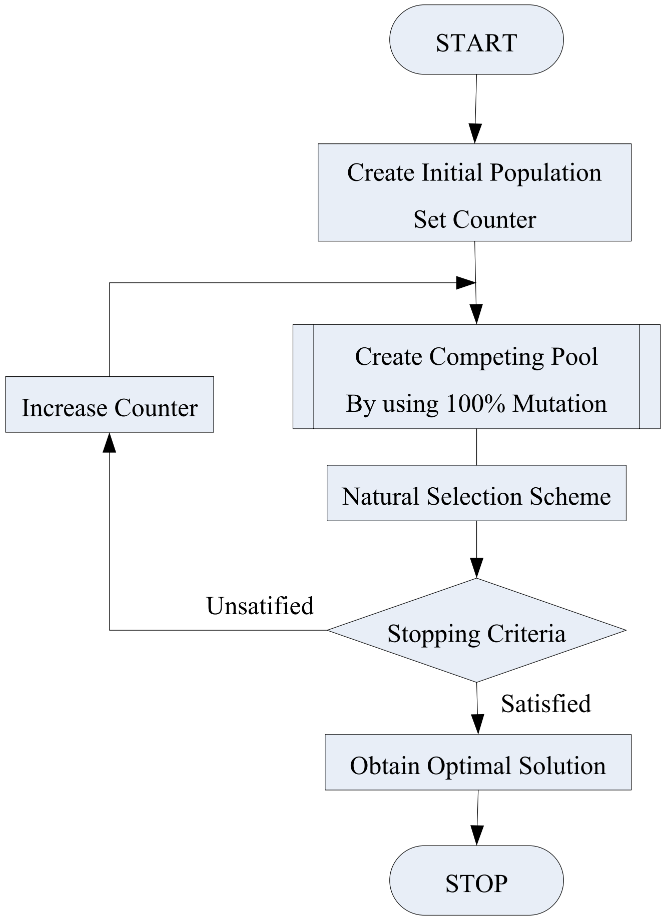

Fig. 2 Flowchart of the EP procedure

3.3 Adaptive tabu search (ATS)

The tabu search method [10, 21] is an iterative process that searches for the best solution by moving from a current solution to find a better solution repeatedly. One of the important features of the TS method is its tabu list that keeps the history of search paths. The information in the list is used for finding a new direction of search movement. Every new is expected to search a better solution and ultimately the optimum one. Another feature of the tabu search method is its aspiration criterion. The aspiration criterion provides preferable characteristics of any possible solutions. It is particularly useful for the selection of a proper solution from a set of satisfied solutions.

In order to improve the performance of the tabu search method, we have proposed two additional mechanisms namely back-tracking and adaptive search radius. The enhanced version of the tabu search method has been named the adaptive tabu search [15,22,23].

Regarding to the intensification mechanism, the back-tracking mechanism allows the search to look backward to some previous solutions stored in the tabu list. This mechanism may become necessary when the search encounters an entrapment caused by a local solution. An alternative solution is then chosen from the current and the previous solutions. With the back-tracked solution, a new search space is created. Given this new search space to explore, the search moves in a new direction away from that approaching the local solution. Note that the new solution chosen here is not necessary to be the best solution within the current search space but it helps the search to escape from an entrapment. This can be summarized briefly as shown in the flowchart of Fig. 3.

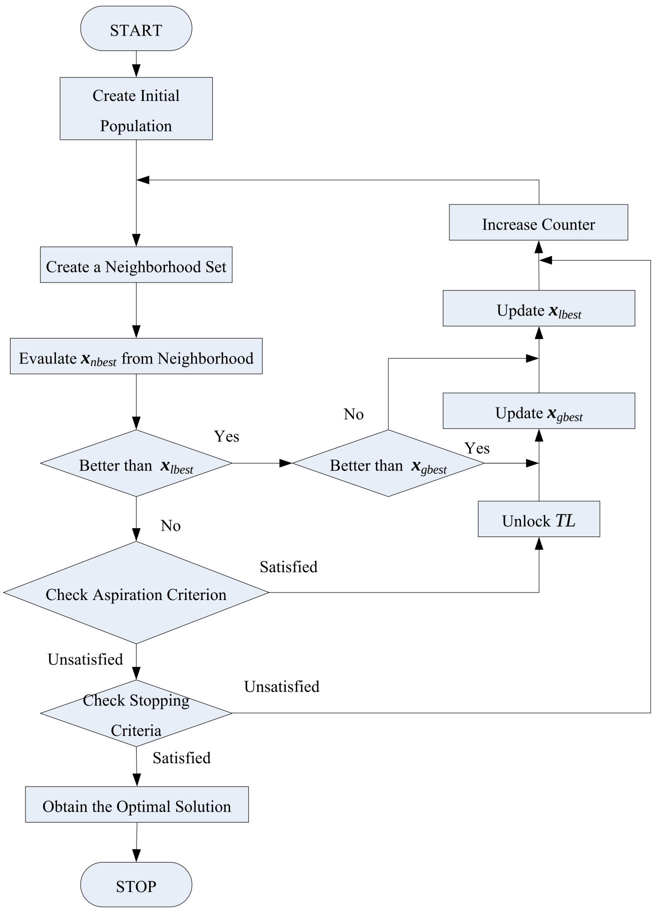

Fig. 3. Flowchart of the ATS procedure

3.4 Particle swarm optimization (PSO)

Kennedy and Eberhart developed a particle swarm optimization algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm [24-29]. Its roots are in zoologist's modeling of the movement of individuals (i.e., fish, birds, and insects) within a group. It has been noticed that members of the group seem to share information among them to lead to increased efficiency of the group. The particle swarm optimization algorithm searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques. Each individual corresponds to a candidate solution to the problem. Individuals in a swarm approach to the optimum through its present velocity, previous experience, and the experience of its neighbors. In a physical n-dimensional search space, the position and velocity of individual i are represented as the velocity vectors. Using these information individual i and its updated velocity can be modified under the following equations in the particle swarm optimization algorithm.

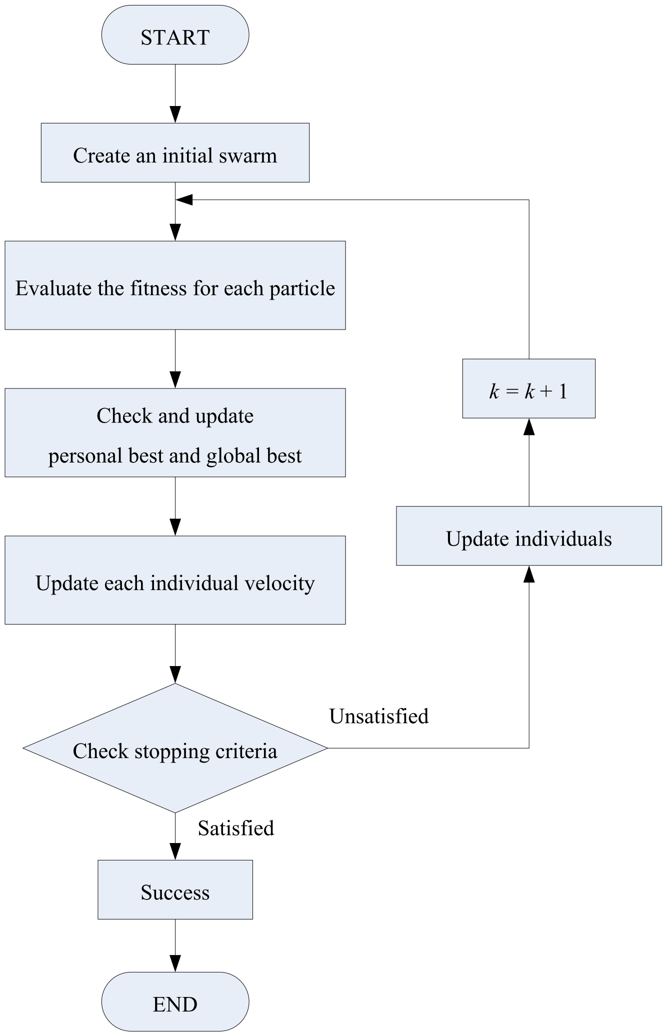

Fig. 4. Flowchart of the PSO procedure

$$\boldsymbol{x}_i^{(k+1)} = \boldsymbol{x}_i^{(k)} + \boldsymbol{v}_i^{(k+1)} \tag{7}$$

$$\boldsymbol{v}_i^{(k+1)} = \boldsymbol{v}_i^{(k)} + \alpha_i \left(\boldsymbol{x}_i^{lbest} - \boldsymbol{x}_i^{(k)} \right) + \beta_i \left(\boldsymbol{x}^{gbest} - \boldsymbol{x}_i^{(k)} \right) \tag{8}$$

Where

$\boldsymbol{x}_i^{(k)}$ is the individual i at iteration k

$\mathbf{v}_i^{(k)}$ is the updated velocity of individual i at iteration k

α_i, β_i are uniformly random numbers between [0,1]

$\mathbf{x}_i^{lbest}$ is the individual best of individual i

$\mathbf{x}^{gbest}$ is the global best of the swarm

The procedure of the particle swarm optimization can be summarized in the flow diagram of Fig. 4.

3.5 Improved harmony search (IHS)

The harmony search algorithm [8] was conceptualized from the musical process of searching for a 'perfect state' of harmony, such as jazz improvisation. Jazz improvisation seeks a best state (fantastic harmony) determined by aesthetic estimation, just as the optimization algorithm seeks a best state (global optimum) determined by evaluating the objective function. Aesthetic estimation is performed by the set of pitches played by each instrument, just as the objective function evaluation is performed by the set of values assigned by each decision variable. The harmony quality is enhanced practice after practice, just as the solution quality is enhanced iteration by iteration. Consider a jazz trio composed of a saxophone, double bass, and guitar. Assume there exists a certain number of preferable pitches in each musician's memory: saxophonist {Do, Mi, Sol}, double bassist {Ti, Sol, Re}, and guitarist {La, Fa, Do}. If the saxophonist plays note Sol, the double bassist plays Ti, and the guitarist plays Do, together their notes make a new harmony (Sol, Ti, Do) which is musically the chord C_7. If this new harmony is better than the existing worst harmony in their memories, the new harmony is included in their memories and the worst harmony is excluded from their memories. This procedure is repeated until a fantastic harmony is found.

However, its first version was invented as a combinatorial optimization where decision variables are discrete. To apply the harmony search method to the real world engineering in which many search spaces are continuous, some procedure of the harmony search method must be modified to be able to handle continuous search variables. Together, the parameter called bandwidth is used and adaptively changed by variance of population. Hence, it is an improved version of the harmony search method which is called as the improved harmony search method [30-34]. The steps in the procedure of harmony search are shown in Fig. 5.

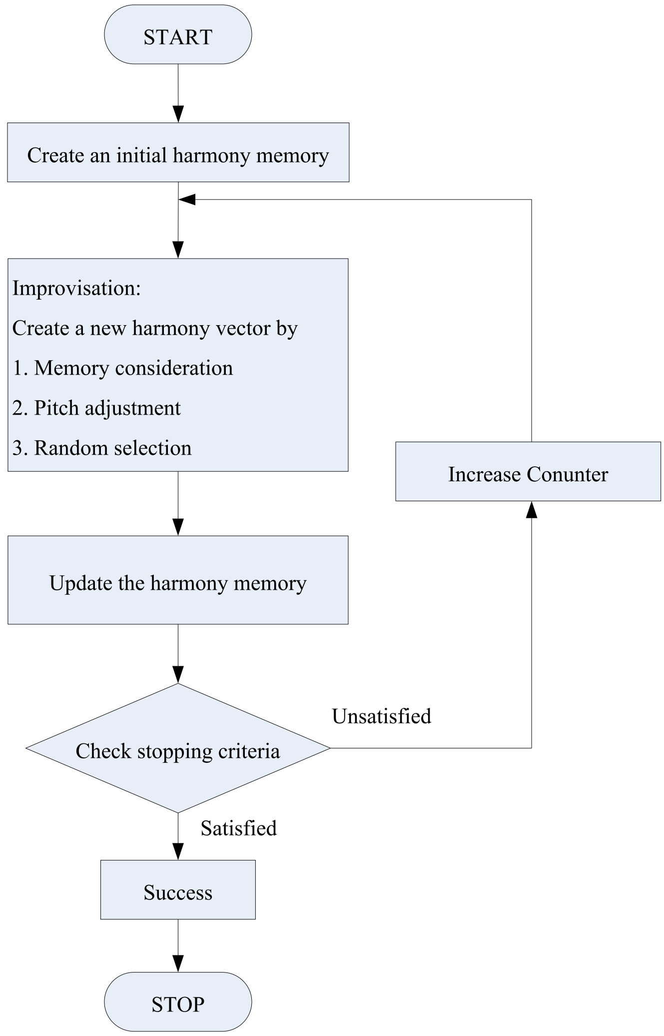

Fig. 5. Flowchart of the IHS procedure

5 Simulation Results

To verify the effectiveness of the proposed improved harmony search method, a six-unit thermal power generating plant acquired from the standard IEEE 30-bus test system was tested. Fuel cost coefficients and generation limits for each generating unit of the test system were given in Table 1.

Table 1: Fuel cost coefficients for each generating unit

i	*a*	*b*	*c*	*D*	*e*	*min*	*max*
1	100	200	10	15	6.283	0.05	0.5
2	120	150	10	10	8.976	0.05	0.6
3	40	180	20	10	14.784	0.05	1.0
4	60	100	10	5	20.944	0.05	1.2
5	40	180	20	5	25.133	0.05	1.0
6	100	150	10	5	18.48	0.05	0.6

The simulations were performed using MATLAB software. The test were carried out by solving economic load dispatch of a single power demand case, P_D = 3.6 p.u.. For comparison purposes, some meta-heuristic search (GA, EP, ATS and PSO) were also applied to solve this test case. The results of which are presented as follows.

5.1 Solution by genetic algorithms

In this case, some parameters must be assigned for the use of genetic algorithms to solve the economic dispatch problems as follows:

- Population size = 20
- Maximum generation = 1000
- Crossover rate = 0.8
- Mutation rate = 0.2

The obtained results for the six-unit system using the genetic algorithms were given in Table 2. It showed that the genetic algorithms has succeeded in finding a global optimal solution for this case.

Table 2: Optimal solution for GA case

P_1	0.4200	P_4	1.0705
P_2	0.3826	P_5	0.6875
P_3	0.7217	P_6	0.3177
F_T = 1704.2 Baht/h			

Fig. 6 showed the convergence of the solution obtained by the genetic algorithms. The total of 500 iterations was spent during this process. The searching process was terminated by the maximum number of generation.

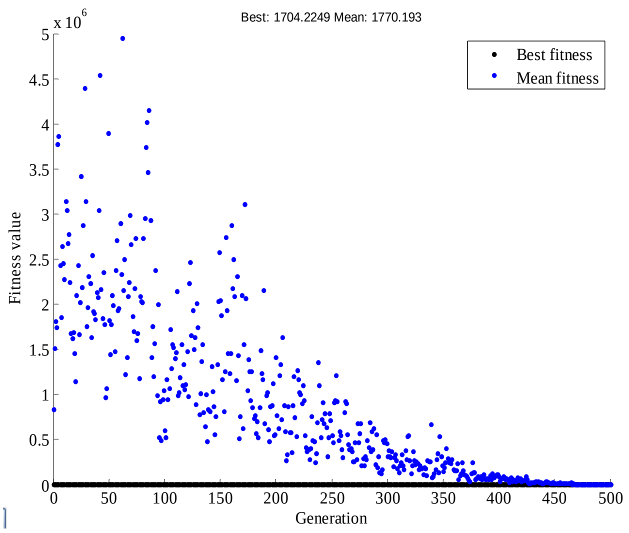

Fig. 6 Solution convergence by GA

5.2 Solution by evolutionary programming

In this case, some parameters must be assigned for the use of evolutionary programming to solve the economic dispatch problems as follows:

- Population size = 20
- Maximum generation = 1000
- Scaling factor β = 0.01

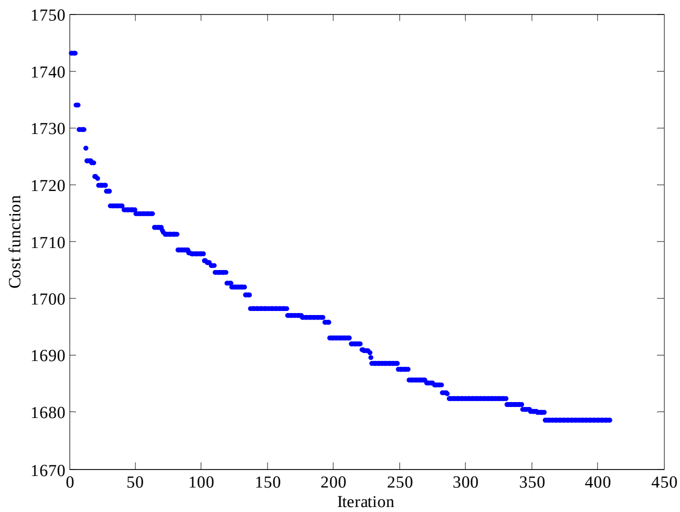

Fig. 7 Solution convergence by GA

The obtained results for the six-unit system using the evolutionary programming were given in Table 3. It showed that the evolutionary programming has succeeded in finding a global optimal solution for this case.

Fig. 7 showed the convergence of the solution obtained by the particle swarm optimization. The total of 412 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

Table 3: Optimal solution for EP case

P_1	0.4189	P_4	0.8581
P_2	0.4946	P_5	0.6354
P_3	0.9611	P_6	0.2320
F_T = 1678.7 Baht/h			

5.3 Solution by adaptive tabu search

In this case, some parameters must be assigned for the use of adaptive tabu search to solve the economic dispatch problems as follows:

- Neighborhood size = 30
- Maximum generation = 1000
- Initial neighborhood radius = 0.05

The obtained results for the six-unit system using the adaptive tabu search were given in Table 4. It showed that the adaptive tabu search has succeeded in finding a global optimal solution for this case.

Table 4: Optimal solution for ATS case

P_1	0.4189	P_4	0.9309
P_2	0.3298	P_5	0.7081
P_3	0.6448	P_6	0.5779
F_T = 1699.7 Baht/h			

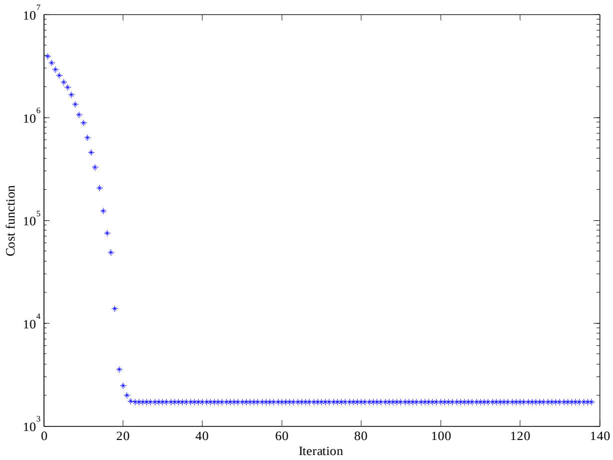

Fig. 8 Solution convergence by ATS

Fig. 8 showed the convergence of the solution obtained by the adaptive tabu search. The total of 138 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

5.4 Solution by particle swarm optimization

In this case, some parameters must be assigned for the use of particle swarm optimization to solve the economic dispatch problems as follows:

- Number of particles = 20
- Maximum generation = 1000
- Maximum velocity = 15

The obtained results for the six-unit system using the particle swarm optimization were given in Table 5. It showed that the particle swarm optimization has succeeded in finding a global optimal solution for this case.

Table 5: Optimal solution for PSO case

P_1	0.0798	P_4	1.1123
P_2	0.4701	P_5	0.5801
P_3	0.9261	P_6	0.4314
F_T = 1702.0 Baht/h			

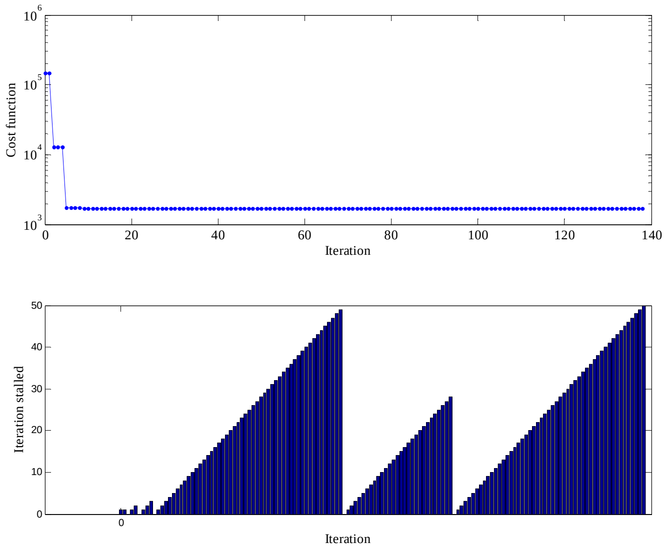

Fig. 9 Solution convergence by PSO

Fig. 9 showed the convergence of the solution obtained by the particle swarm optimization. The total of 136 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

5.5 Solution by improved harmony search

In this case, some parameters must be assigned for the use of improved harmony search to solve the economic dispatch problems as follows:

- Maximum generation = 5000
- Harmony memory size = 20
- Maximum stalled generation = 250

The obtained results for the six-unit system using the improved harmony search were given in Table 6. It showed that the improved harmony search has succeeded in finding a global optimal solution for this case.

Table 6: Optimal solution for IHS case

P_1	0.1899	P_4	1.0449
P_2	0.4679	P_5	0.6330
P_3	0.9096	P_6	0.3571
F_T = 1696.0 Baht/h			

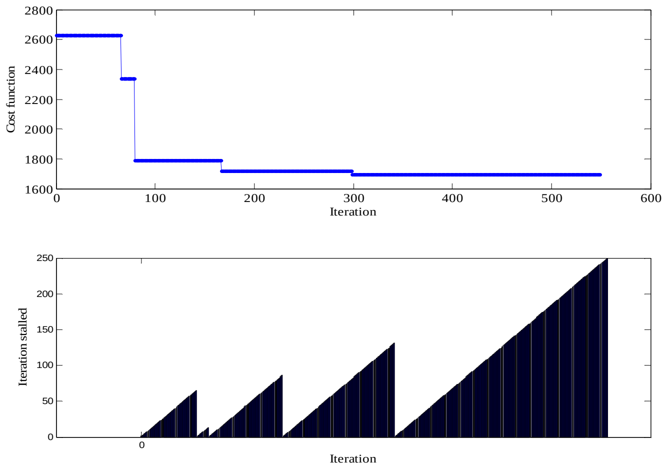

Fig. 10 Solution convergence by IHS

Fig. 10 showed the convergence of the solution obtained by the improved harmony search. The total of 550 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

6 Conclusion

Solution methods of economic dispatch problems are described in this paper. Some efficient meta-heuristic search methods (genetic algorithm, evolutionary programming, adaptive tabu search, particle swarm optimization and improved harmony search) are briefed and summarized, step-by-step in the flow diagrams. The results showed that a set of optimal dispatch solutions with respect to the economic objective can be efficiently found. As a result, the improved harmony search method proves that it can find a place among some efficient meta-heuristic search methods in order to find a near global solution of the economic load dispatch problems.

References:

[1] J. Nocedal and S.J. Wright, *Numerical Optimization*, Springer, 2006.

[2] E.G. Talbi, *Metaheuristics: from design to implementation*, Wiley, 2009.

[3] D.P. Kothari and J.S. Dhillon, *Power System Optimization*, Prentice-Hall of India, 2006.

[4] J. B. Park, K. S. Lee, J. R. Shin, and K. Y. Lee, A particle swarm optimization for economic dispatch with nonsmooth cost functions, *IEEE Trans. on Power Systems*, Vol. 20, No. 1, pp. 34-42, Feb. 2005.

[5] H. Altun and T. Yalcinoz, Implementing soft computing techniques to solve economic dispatch problem in power systems, *An International of Expert Systems with Applications*, Vol. 35, Issue 4, pp. 1668 – 1678, 2008.

[6] A.J. Wood and B.F. Wollenberg, *Power Generation, Operation and Control*, New York, Wiley, 1984.

[7] J.J. Fogel, A.J. Owens, and M.J. Walsh, *Artificial Intelligence through Simulated Evolution*, John Wiley, 1966.

[8] Z.W. Geem, J.H. Kim and G.V. Loganathan, *A new heuristic optimization algorithm: harmony search, Simulation*, vol. 76, No. 60, 2001.

[9] T. Bouktir, R. Labdani and L. Slimani, Economic power dispatch of power system with pollution control using multi-objective particle swarm optimization, *University of Sharjah Journal of Pure & Applied Sciences*, Vol. 4, No. 2, pp. 57-77, 2007.

[10] T. Kulowrawanichpong and S. Sujitjorn, Optimal power flow using Tabu search, *IEEE Power Engineering Review*, Power Engineering Letter, pp. 37- 40, 2002.

[11] D.E. Goldberg, and D. Edward, *Genetic Algorithms in Search, Optimization and Machine Learning*, Wiley, 1989.

[12] The MathWorks Inc., *Genetic Algorithms and Direct Search TOOLBOX*, CD-ROM Manual, 2004.

[13] K. Somsai, A. Oonsivilai, A. Srikaew, and T. Kulworawanichpong, Optimal PI controller design and simulation of a static var compensator using MATLAB's SIMULINK, *The 7th WSEAS International Conference on POWER SYSTEMS*, Beijing, China, pp. 30 – 35.

[14] T. Charuwat, T. Kulworawanichpong, Genetic based distribution service restoration with minimum average energy not supplied, *The 8th International Conference on Adaptive and Natural Computing Algorithms (ICANNGA2007)*, 11–14 April 2007, pp. 230-239.

[15] T. Kulworawanichpong, K-L. Areerak, K-N. Areerak, P. Pao-la-or, P. Puangdownreong, S. Sujitjorn, Dynamic parameter identification of induction motors using intelligent search techniques, *The 24th IASTED Int. Conf. Modelling, Identification, and Control (MIC 2005)*, Austria 2005, pp. 328-332.

[16] M. Dubey, N. E. Mastorakis, Tunning of Fuzzy Logic Power System Stabilizers using Genetic Algorithm in Multimachine Power System, *The WSEAS Transaction on Power Systems*, Issue 3, Vol. 4, pp. 105 – 114, 2009

[17] P. Venkatesh, R. Gnanadass, and N. P. Padhy, Comparison and Application of Evolutionary Programming Techniques to Combined Economic Emission Dispatch With Line Flow Constraints, *IEEE Trans. Power Syst.*, vol. 18, pp. 688-697, May 2003.

[18] K.P. Wong and J. Yuryevich, Evolutionary-programming based algorithm for environmentally constrained economic dispatch, *IEEE Trans. Power Syst.*, vol.13, pp. 301-306, May 1998.

[19] P. Venkatesh, K. Y. Lee, Multi-Objective Evolutionary Programming for Economic Emission Dispatch problem, *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century*, 2008, pp. 1-8.

[20] P. Somasundaram and K. Kuppusamy, Application of evolutionary programming to security constrained economic dispatch, *Electrical Power and Energy Systems*, 27, 2005, pp. 343–351.

[21] F. Glover and M. Laguna. *Tabu Search*, Kluwer, 1997.

[22] T. Kulworawanichpong, K-N. Areerak, and S. Sujitjorn, Moving towards a new era of intelligent protection through digital relaying in power systems, *Lecture Notes in Artificial Intelligences*, LNAI 3215 Part I, pp. 1255 – 1261, 2004

[23] T. Kulworawanichpong, K-L. Areerak, K-N. Areerak and S. Sujitjorn, Harmonic Identification for Active Power Filters Via Adaptive Tabu Search Method, *Lecture Notes in Artificial Intelligences*, LNAI 3215 Part I, pp. 687–694, 2004.

[24] J. Kennedy and R.C. Eberhart, *Swarm Intelligence.* Morgan Kaufmann, 2001.

[25] K. Thanushkodi, S. Muthu Vijaya Pandian, R. S. Dhivy Apragash, M. Jothikumar, S. Sriramnivas, K. Vinodh, An Efficient Particle Swarm Optimization for Economic Dispatch Problems With Non-smooth cost functions, *The WSEAS Transaction on Power Systems*, Issue 4, Vol. 3, pp. 257 – 266, 2008.

[26] A. Oonsivilai, B. Marungsri, Stability Enhancement for Multi-machine Power System by Optimal PID Tuning of Power System Stabilizer using Particle Swarm Optimization, *The WSEAS Transaction on Power Systems*, Issue 6, Vol. 3, pp. 465 – 474, 2008.

[27] J. Zahavi, L. Eisenbergerg, Economic environmental power dispatch, *IEEE Trans. Syst. Man*, Cybern. SMC-5, 1975.

[28] J. Cadogan, L. Eisenberg, SO2 emission management for electric power systems, *IEEE Trans. PAS*, 96 (2), pp. 393-401, 1977.

[29] L. Wang, C. Singh, Reserve-constrained multiarea environmental/ economic dispatch based on particle swarm optimization with local search, *Engineering Applications of Artificial Intelligence*, 22, 2009, pp. 298–307.

[30] S.L. Kang, and Z.W. Geem, “A new structuraloptimization method based on the harmony search algorithm,” *Comput. Struct.* Vol. 82, No.9–10, pp. 781–798, 2004.

[31] K. S. Lee, Z. W. Geem, “A new meta-heuristic algorithm for continuous engineering optimization: harmony search theory and practice,” *Comput. Methods Appl. Mech. Engg.*, Vol. 194, pp. 3902–3933, 2005.

[32] M. Mahdavi, M. Fesanghary, E. Damangir, “An improved harmony search algorithm for solving optimization problems,” *Applied Mathematics and Computation*, Vol. 188, pp. 1567–1579, 2007.

[33] M.G.H. Omran, M. Mahdavi, “Global-best harmony search,” *Applied Mathematics and Computation*,Vol. 198, pp. 643–656, 2008.

[34] V.R. Pandi, B.K. Panigrahi, M.K. Mallick, A. Abraham, S. Das, Improved Harmony Search for Economic Power Dispatch, *The 9th International Conference on Hybrid Intelligent Systems*, pp. 403-408, 2009