Combined Economic and Emission Dispatch Using Particle Swarm Optimization

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Abstract: - This paper presents a demonstration of solving combined economic and emission dispatch problems by using one of swarm intelligences, called particle swarm optimization. The objective of the combined problem can be expressed by taking both the total production cost and total emission into account with required constraints. Among potential intelligent search methods, particle swarm optimization is well-known and widely-used in solving economic load dispatch. In this paper, the particle swarm optimization is exploited to demonstrate its use. A three-unit thermal power plant is situated for test. Sets of suitable dispatch with respect to economic or emission objectives can be efficiently found.

Key-Words: - Economic dispatch, emission dispatch, fuel cost function, total emission function, particle swarm optimization

1 Introduction

Economic load dispatch is one of the main functions in electrical power system operation, management and planning [1,2]. Security, reliability, economy and stability are characterized and included to form the dispatching objective or constraints in various forms. Typically, the main objective of economic load dispatch is to minimize the total production cost of the generating system while the required equality and inequality constraints must be satisfied. Nowadays, energy sources to produce mechanical power applied to the rotor shaft of generating units are of fossil fuels. This can cause a vast amount of carbon dioxide (CO2), sulfur dioxide (SO2) and nitrogen oxides (NOx) emissions in which atmospheric pollution is created [3]. Emission control over environmental pollution caused by fossil-fired generating units and the enforcement of environmental regulations [4] has received careful attention. May research work in generation allocation of thermal power plants have emphasized the essence of pollution control in electrical power systems [4-14].

However, taking only the operation of minimum environmental impact is impractical due to causing the higher production cost of the system. On the other hand, to operate the generating system with the minimum of total production cost is not met the emission requirement. Therefore, economic dispatch, emission dispatch or combined economic and emission dispatch is somehow chosen individually or merged all together. To find the appropriate solution to this question, a good power management strategy is set. Several optimization techniques such as lambda iteration, linear programming, non-linear programming, quadratic programming, interior point method or even intelligent search methods (e.g. genetic algorithm, evolutionary programming, particle swarm optimization, etc [1,3,6,13]) are employed for solving the various economic dispatch problems and also the unit commitment problems [15].

The solution of economic dispatch problems using genetic algorithm required a large number of generations when the power generating system has the large number of units. Combined economic and emission dispatch has been proposed in the field of power generation dispatch, which simultaneously minimizes both fuel cost and total emissions. When the emission is minimized the fuel cost may be unacceptably high or when the fuel cost is minimized the emission may be high. In literature as environmental economic dispatch or emission dispatch, many algorithms are used to solve such a problem. A cooling mutation technique in EP algorithm to solve CEED problem for nine units system was proposed [18]. However, [19] showed that particle swarm optimization is superior to those intelligent search techniques mentioned previously.

Proposed methods in [20, 21] convert a multiobjective problem into a single objective problem by assigning different weights to each objective. This allows a simpler minimization process but does require the knowledge of the relative importance of each objective and the explicit relationship between the objectives usually does not exist.

In this paper two objectives are simultaneously minimize through the provision of the weighting factors. Section 2 illustrates economic and emission dispatch problems with corresponding mathematical expressions. Section 3 gives the brief of particle swarm optimization and its calculation procedure step-by-step. Section 4 is the simulation results and discussion. Conclusion remark is in Section 5.

2 Problem Formulation

Real power generation can be allocated to available generating units in many different ways. In this paper, only economic and emission objectives are considered as follows. As the name implies, the combined economic and emission dispatch problems consist of two main problems. Each of which can be solved separately, however this leads to carelessness of environmental impact of gas emission from electricity production if only the economic objective is taken into account and vice versa. Before describing the combined problem, the two objectives must be explained separately and then the combined function as follows.

2.1 Economic dispatch

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.

The economic dispatch problem [2, 22] 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. Most of the problem given in the economic dispatch concerns with fossil fuel-fired thermal power plants. A thermal power plant is a power plant in which its prime-mover is driven by steam. Water is the working fluid. It is heated at the boiler and circulated with energy to be expanded at the steam turbine to give work to the rotor shaft of the generator. After it passes through the turbine, it is condensed in a condenser and then pumped to feed the boiler where it is heated up. This is known as a Rankine cycle as described in Fig. 1 and Fig. 2.

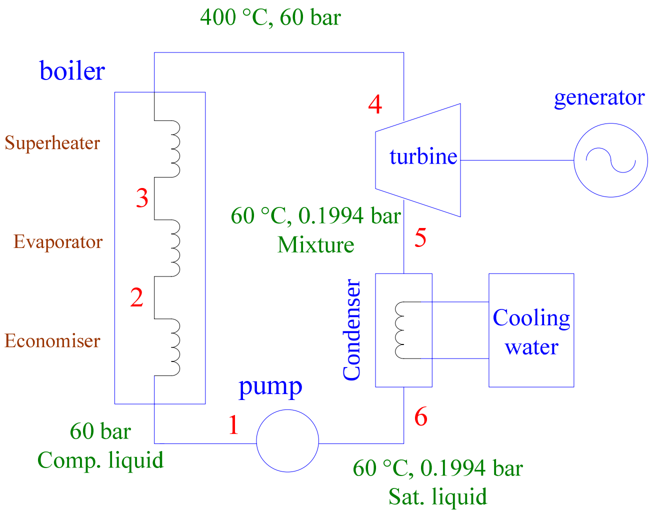

Fig. 1. Structure of a thermal power plant

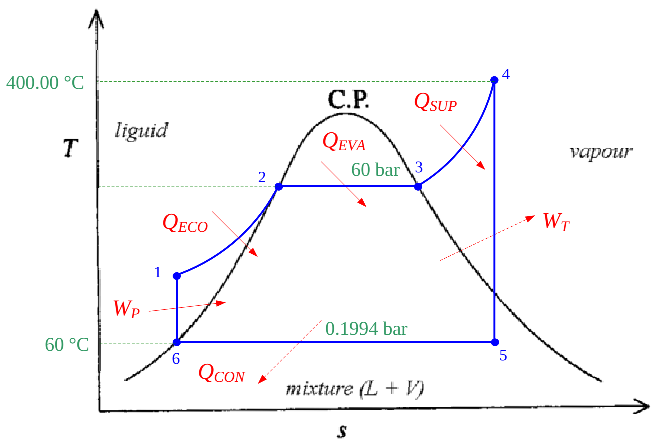

Fig. 2. T-s diagram of a thermal power plant

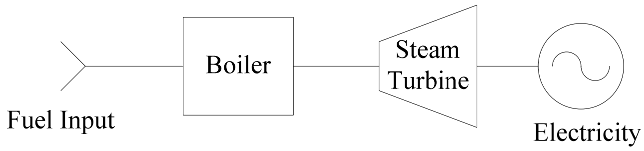

Fig. 3. Energy conversion diagram of the thermal power plant

For simplification, thermal power plants can be modeled as a transfer function of energy conversion from fossil fuel to electricity as described in Fig. 3. An amount of fuel used to produce required electric power is considered in form of fuel price. Therefore, 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.

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

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 non-linear valve-point loading effect [19] is included. Fig. 4 explains characteristic of a smooth fuel-cost curve while non-linear valve-point loading effect is presented in Fig. 5. To simplify the fuel-cost function, any smooth fuel-cost curve can be expressed in form of quadratic functions while a sinusoidal term represents valve-point effect.

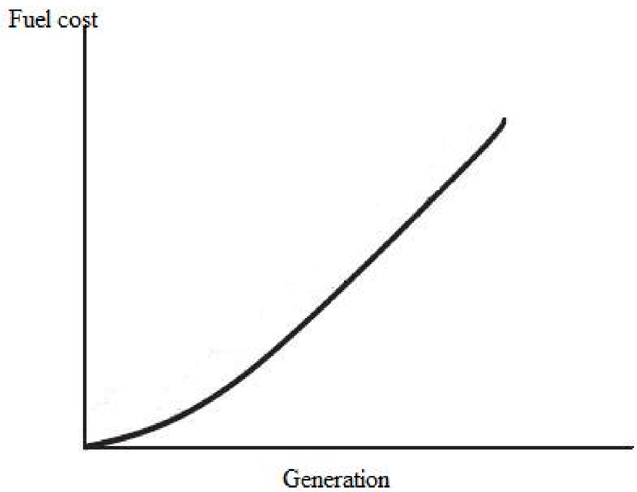

Fig. 4. Example of a smooth fuel-cost curve

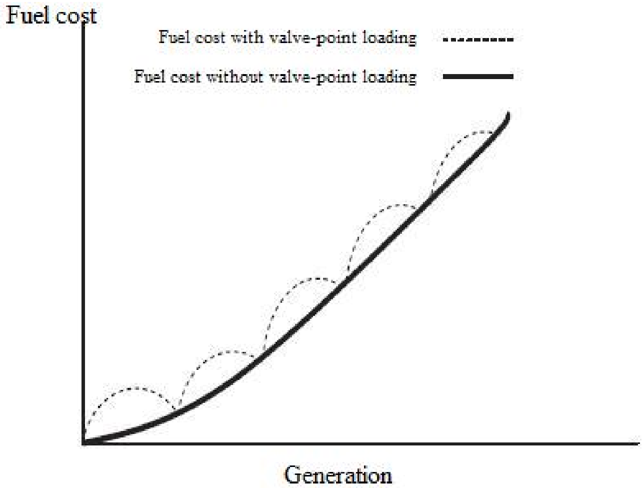

Fig. 5. Representation of a nonlinear valve-point effect

2.2 Emission dispatch

A fossil-fuel power station is a power station that burns fossil fuels such as coal, natural gas or petroleum (oil) to produce electricity. Fossil-fuel power station are designed on a large scale for continuous operation. In many countries, such plants provide most of the electrical energy used. Fossil fuel power stations have some kind of rotating machinery to convert the heat energy of combustion into mechanical energy, which then operate an electrical generator. The prime mover may be a steam turbine, a gas turbine or, in small isolated plants, a reciprocating internal combustion engine. Some thermal plants have the intermediate step of using the heat from combustion to produce steam, reducing overall efficiency of electricity production. All plants use the drop between the high pressure and temperature of the steam or com busting fuel and the lower pressure of the atmosphere or condensing vapour in the steam turbine.

Byproducts of power thermal plant operation need to be considered in both the design and operation. Sometimes waste heat due to the finite efficiency of the power cycle, when not recovered and sold as steam or hot water, must be released to the atmosphere, often using a cooling tower, or river or lake water as a cooling medium, especially for condensing steam. The flue gas from combustion of the fossil fuels is discharged to the air; this contains carbon dioxide and water vapour, as well as other substances such as nitrogen, nitrogen oxides, sulfur oxides, and (in the case of coal-fired plants) fly ash and mercury. Solid waste ash from coal-fired boilers must also be removed, although some coal ash can be recycled for building materials.

Fossil fueled power stations are major emitters of greenhouse gases (GHG) which according to the consensus of scientific organisations are a major contributor to the global warming observed over the last 100 years. Brown coal emits 3 times as much GHG as natural gas, black coal emits twice as much. Efforts exist to use carbon capture and storage of emissions but these are not expected to be available on a commercial scale and economically viable basis by 2025.

The complete combustion of fossil fuel using air as the oxygen source is summarized in the following chemical reaction, assuming the nitrogen remains inert. Depending on temperature and flame parameters during combustion, however some of the nitrogen can be oxidized, producing various nitrogen oxides. Other, unintended, products of combustion are sulfur dioxide coming from sulfur impurities (predominantly in coal).

$$C_xH_y + \left(x+\frac{y}{4}\right)O_2 + 3.76\left(x+\frac{y}{4}\right)N_2 \rightarrow Heat + xCO_2 + \frac{y}{2}H_2O + 3.76\left(x+\frac{y}{4}\right)N_2$$

$$Fuel + Oxygen \rightarrow Heat + Carbondioxide + Water$$

As the combustion flue gas exits the boiler it is routed through a rotating flat basket of metal mesh which picks up heat and returns it to incoming fresh air as the basket rotates, This is called the air pre-heater. The gas exiting the boiler is laden with fly ash, which are tiny spherical ash particles. The flue gas contains nitrogen along with combustion products carbon dioxide, sulfur dioxide, and nitrogen oxides. The fly ash is removed by fabric bag filters or electrostatic precipitators. Once removed, the fly ash byproduct can sometimes be used in the manufacturing of concrete. This cleaning up of flue gases, however, only occurs in plants that are fitted with the appropriate technology. Still, the majority of coal fired power plants in the world do not have these facilities. Legislation in Europe has been efficient to reduce flue gas pollution. Japan has been using flue gas cleaning technology for over 30 years and the US has been doing the same for over 25 years. China is now beginning to grapple with the pollution caused by coal fired power plants. Where required by law, the sulfur and nitrogen oxide pollutants are removed by stack gas scrubbers which use a pulverized limestone or other alkaline wet slurry to remove those pollutants from the exit stack gas. Other devices use catalysts to remove

Nitrous Oxide compounds from the flue gas stream. The gas travelling up the flue gas stack may by this time have dropped to about 50 °C (120 °F). A typical flue gas stack may be 150–180 metres (490–590 ft) tall to disperse the remaining flue gas components in the atmosphere. The tallest flue gas stack in the world is 419.7 metres (1,377 ft) tall at the GRES-2 power plant in Ekibastuz, Kazakhstan. In the United States and a number of other countries, atmospheric dispersion modeling studies are required to determine the flue gas stack height needed to comply with the local air pollution regulations. The United States also requires the height of a flue gas stack to comply with what is known as the "Good Engineering Practice (GEP)" stack height. In the case of existing flue gas stacks that exceed the GEP stack height, any air pollution dispersion modeling studies for such stacks must use the GEP stack height rather than the actual stack height.

The world's power demands are expected to rise 60% by 2030. With the worldwide total of active coal plants over 50,000 and rising, the International Energy Agency (IEA) estimates that fossil fuels will account for 85% of the energy market by 2030. World organizations, and international agencies like the IEA are concerned about the environmental impact of burning fossil fuels, and coal in particular. The combustion of coal contributes the most to acid rain and air pollution, and has been connected with global warming. Due to the chemical composition of coal there are difficulties in removing impurities from the solid fuel prior to its combustion. Modern day coal power plants pollute very little due to new technologies in "scrubber" designs that filter the exhaust air in smoke stacks. Nowadays, the only pollution caused from coal-fired power plants comes from the emission of gases—carbon dioxide,nitrogen oxides, and sulfur dioxide into the air. Acid rain is caused by the emission of nitrogen oxides and sulfur dioxide into the air. These themselves may be only mildly acidic, yet when they react with the atmosphere, they create acidic compounds (such as sulfurous acid, nitric acid, and sulfuric acid) that fall as rain, hence the term acid rain. In Europe and the U.S.A., stricter emission laws and decline in heavy industries have reduced the environmental hazards associated with this problem, leading to lower emissions after their peak in 1960s. Electricity generation using carbon based fuels is responsible for a large fraction of carbon dioxide (CO_2) emissions worldwide; and for 41% of U.S. man-made carbon dioxide emissions. Of fossil fuels, coal combustion in thermal power stations result in greater amounts of carbon dioxide emissions per unit of electricity generated (2249 lbs/MWh) while oil produces less (1672 lb/(MW·h) or 211 kg/GJ) and natural gas produces the least 1135 lb/(MW·h) (143 kg/GJ). The Intergovernmental Panel on Climate Change (see IPCC) states that carbon dioxide is a greenhouse gas and that increased quantities within that atmosphere will lead to higher average temperatures in a global sense (global warming); concerns regarding the potential for such warming to change the global climate prompted IPCC recommendations calling for large cuts to CO_2 emissions worldwide. Emissions may be reduced through more efficient and higher combustion temperature and through more efficient production of electricity within the cycle. Carbon capture and storage (CCS) of emissions from coal fired power stations is another alternative but the technology is still being developed and will increase the cost of fossil fuel-based production of electricity. CCS may not be economically viable, unless the price of emitting CO_2 to the atmosphere rises.

The solution of economic dispatch problem [1,3,12] will give the amount of active power to be generated by different units at the minimum production cost for a particular demand. However, the total amount of pollutant emission is not included in classical economic dispatch problem. The total amount of pollutant emission from a fossil-fired thermal generating unit depends upon the amount of power generated by each unit [23]. For simplification, the total emission generated can be approximately modeled as a direct sum of a quadratic function and an exponential term of the active power output of the generating units. The pollutant emission dispatch problem can be described as the optimization of total amount of pollutant emission defined by the following equation.

$$E_T = \sum_{i=1}^{N_G} \left\{ \alpha_i P_i^2 + \beta_i P_i + \gamma_i + \xi_i e^{\tau_i P_i} \right\} \tag{2}$$

Where

N_G is the total number of generating units

E_T is the total pollutant emission

P_i is the power output of generating unit i

α_i, β_i, γ_i, ξ_i, τ_i are emission coefficients of unit i

2.3 Combined economic and emission dispatch

The economic dispatch and emission dispatch are two different problems. Emission dispatch can be included in conventional economic load dispatch problems by adding an emission constraint into the problem. In this paper, the two objectives can be converted into a single objective function [12,17] by introducing a price penalty factor as defined follows.

$$h = \frac{F_T\left(P_i^{\max}\right) / P_i^{\max}}{E_T\left(P_j^{\max}\right) / P_j^{\max}} \tag{3}$$

Where

h is the price penalty factor
i is the highest fuel-cost unit
j is the highest pollutant-emission unit

The combined objective function of the economic and emission dispatch is assigned by the following expression.

$$\Phi_T = w_{eco} F_T + w_{emi} h E_T \tag{4}$$

Where
Φ_T is the combined objective function
w_{eco}, w_{emi} are weighting factors.

The two weighting factors can be given in many forms. The case of w_{eco} = 1.0 and w_{emi} = 0.0 is to yield the classical economic dispatch problem while the pure emission dispatch is the case of w_{eco} = 0.0 and w_{emi} = 1.0. To establish the combined economic and emission dispatch problem, both weighting factors must be equal, for example w_{eco} = 0.5 and w_{emi} = 0.5.

2.4 Problem constraints

There are equality and inequality constraints [2]. In this kind of problems, a power balance equation (5) is set as an equality constraint whereas the limits of power generation output (6) are inequality constraints.

$$P_D + P_{Loss} - \sum_{i=1}^{N_G} P_i = 0 \tag{5}$$

$$P_i^{\min} \le P_i \le P_i^{\max},\ i = 1, 2, \cdots, N_G \tag{6}$$

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*

3 Particle Swarm Optimization based Optimal Solution of Combined Economic and Emission Dispatch Problems

Kennedy and Eberhart developed a particle swarm optimization (PSO) algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm [6,19, 24]. 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.

The PSO belongs to the class of direct search methods used to find an optimal solution to an objective function (aka fitness function) in a search space. Direct search methods are usually derivative-free, meaning that they depend only on the evaluation of the objective function. The particle swarm optimization algorithm is simple, in the sense that even the basic form of the algorithm yields results, it can be implemented by a programmer in short duration, and it can be used by anyone with an understanding of objective functions and the problem at hand without needing an extensive background in mathematical optimization theory. The PSO is a stochastic, population-based computer algorithm modeled on swarm intelligence. Swarm intelligence is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. Social influence and social learning enable a person to maintain cognitive consistency. People solve problems by talking with other people about them, and as they interact their beliefs, attitudes, and behaviors change; the changes could typically be depicted as the individuals moving toward one another in a socio-cognitive space. Particle swarm optimization is inspired by this kind of social optimization. A problem is given, and some way to evaluate a proposed solution to it exists in the form of a fitness function. A communication structure or social network is also defined, assigning neighbors for each individual to interact with. Then a population of individuals defined as random guesses at the problem solutions is initialized. These individuals are candidate solutions. They are also known as the particles, hence the name particle swarm. An iterative process to improve these candidate solutions is set in motion. The particles iteratively evaluate the fitness of the candidate solutions and remember the location where they had their best success. The individual's best solution is called the particle best or the local best. Each particle makes this information available to their neighbors. They are also able to see where their neighbors have had success. Movements through the search space are guided by these successes, with the population usually converging, by the end of a trial, on a problem solution better than that of non-swarm approach using the same methods.

The PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA) [25]. The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called lbest. when a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest. The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its pbest and lbest locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations. In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

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.

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

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

Where

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

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

α_i, β_i are uniformly random numbers in a range of [0,1]

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

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

The procedure of the particle swarm optimization can be summarized in the flow diagram of Fig. 1.

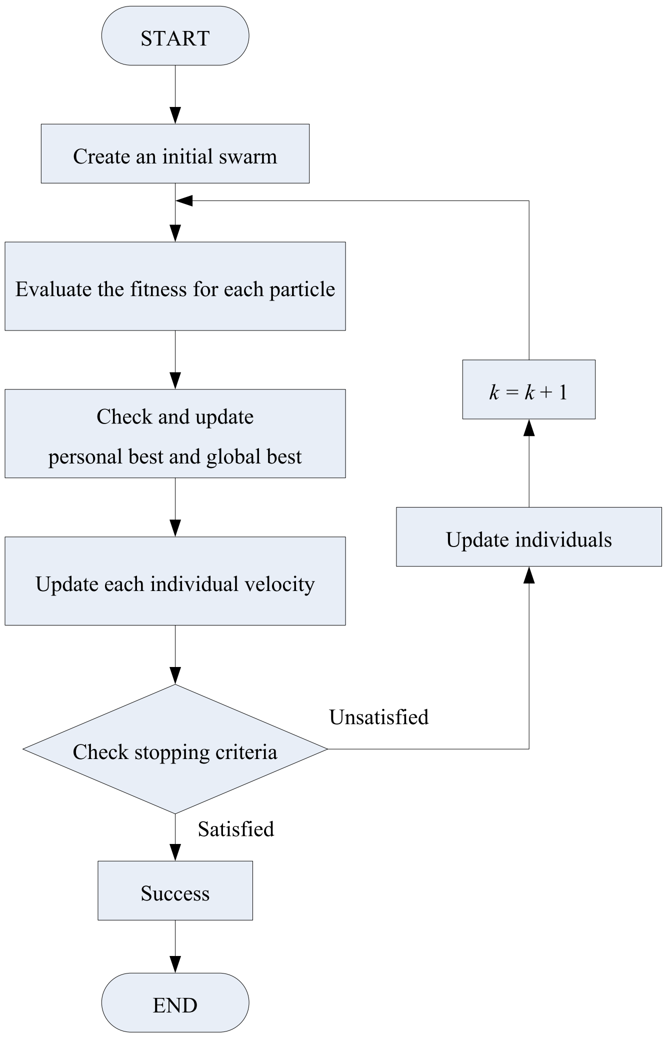

Fig. 1. Flow diagram of particle swarm optimization

Moreover, the pseudo code of the procedure can be written as follows.

```
I) For each particle:
      Initialize particle

II) Do:
    a) For each particle:
       1) Calculate fitness value
       2) If the fitness is better than the best fitness in history
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            3) Set current value as the new population best
            End
         b) For each particle:
            1) Find the particle neighborhood and the best fitness particle
            2) Calculate particle velocity according to the velocity equation
            3) Apply the velocity constriction
            4) Update particle position according to the position equation (2)
            5) Apply the position constriction
            End
      While maximum iterations or minimum error criteria is not attained
```

5 Simulation Results

To verify the effectiveness of the proposed particle swarm optimization method, a three-unit thermal power generating plant was tested. Fuel cost coefficients and generation limits for each generating unit of the test system were given in Table 1. Table 2 presented pollutant emission coefficients of each generating unit.

Table 1: Fuel cost coefficients

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

Table 2: Emission coefficients

i	α	β	γ	ξ	τ
1	6.490	-5.554	4.091	2×10^{-4}	2.857
2	5.638	-6.047	2.543	5×10^{-4}	3.333
3	4.586	-5.094	4.258	1×10^{-6}	8.000

Some parameters must be assigned for the use of particle swarm optimization to solve combined economic and emission dispatch problems as follows:

- Number of particles = 50
- Maximum generation = 1000
- Maximum generation stalled = 50
- Maximum velocity = 15

The simulations were performed using MATLAB software. The results obtained from particle swarm optimization of solving combined economic and emission dispatch problems described in this paper can be divided into three test cases as follows.

5.1 Case 1: Pure Economic Objective

In this case, the weighting factors were given by,

$w_{eco} = 1.0$

$w_{emi} = 0.0$

The obtained results for the three-unit system using the particle swarm optimization were given in Table 3. It showed that the particle swarm optimization has succeeded in finding a global optimal solution for this case.

Table 3: Optimal solution for test case 1

P_1	P_2	P_3	F_T	E_T	Φ_T
0.3595	0.1918	0.6482	790.98	38.02	790.98

Fig. 2 showed the convergence of the solution obtained by the particle swarm optimization. The total of 84 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

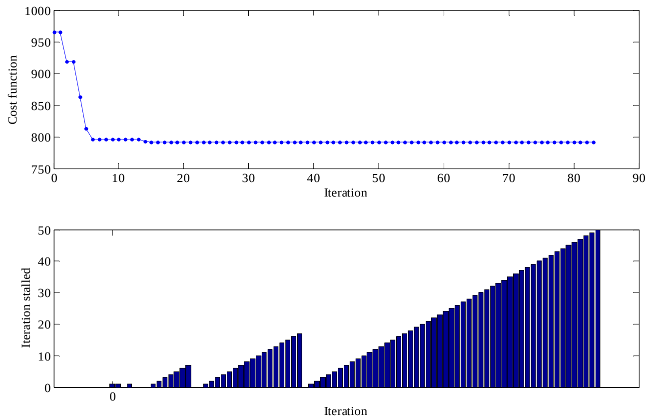

Fig. 2 Solution convergence of test case 1

5.2 Case 2: Pure Emission Objective

In this case, the weighting factors were given by,

$w_{eco} = 0.0$

$w_{emi} = 1.0$

The obtained results for the three-unit system using the particle swarm optimization were given in Table 4. It showed that the particle swarm optimization has succeeded in finding a global optimal solution for this case.

Table 4: Optimal solution for test case 2

P_1	P_2	P_3	F_T	E_T	Φ_T
0.2804	0.1443	0.7751	813.02	37.35	399.98

Fig. 3 showed the convergence of the solution obtained by the particle swarm optimization. The total of 126 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

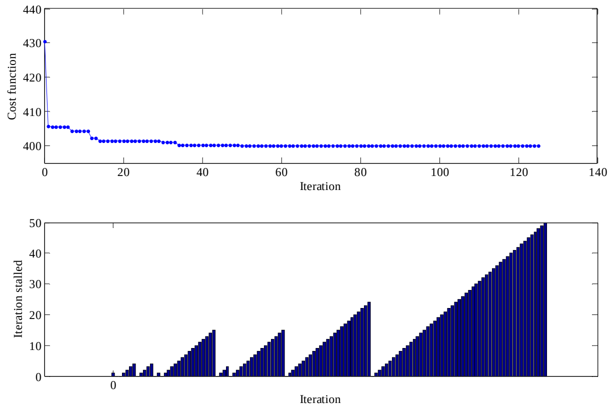

Fig. 3 Solution convergence of test case 2

5.3 Case 3: Combined Economic and Emission Objective

In this case, the weighting factors were given by,

$$w_{eco} = 1.0$$
$$w_{emi} = 1.0$$

The obtained results for the three-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 test case 2

P_1	P_2	P_3	F_T	E_T	Φ_T
0.0527	0.2007	0.9468	794.07	38.27	1203.9

Fig. 4 showed the convergence of the solution obtained by the particle swarm optimization. The total of 84 iterations was spent during this process. The searching process was terminated by the maximum number of stalled generation.

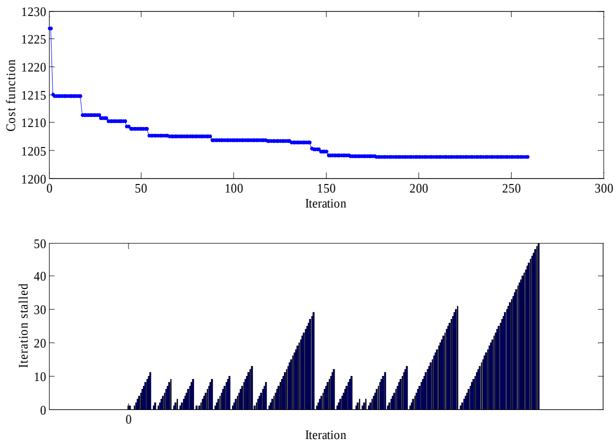

Fig. 4 Solution convergence of test case 3

6 Conclusion

Economic and emission dispatch problems are combined and converted into a single objective function. The converted objective function is minimized based on efficient particle swarm optimization. The results showed that sets of suitable dispatch with respect to economic or emission objectives can be efficiently found.

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