



(RESEARCH ARTICLE)



Application of Particle Swarm Optimization in Solving Economic Dispatch with Multiple Fuel Options

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Abstract

Minimizing electricity generation cost which includes fuel cost, emission cost, operation/maintenance cost and network loss cost of multiple operating units has been a major issue in the power sector. The economic dispatch has the objective of allocating different loads to the power generators in such a manner that the total fuel cost is minimized while all operating constraints are satisfied. Conventional optimization methods assume generator cost curves to be continuous and monotonically increasing, but modern generators have a variety of nonlinearities in their cost curves making this assumption inaccurate, and the resulting approximate dispatches cause a lot of revenue loss. Computational intelligence optimization like Particle Swarm Optimization performs better for such problems. To know the effectiveness and efficiency in solving economic dispatch, this paper proposes the application of particle swarm optimization. The mathematical model of economic dispatch is developed and then, Particle Swarm Optimization is developed to solve the economic dispatch problem using 3-generator and 6-generator system with multiple fuel option. The test results clearly demonstrated that particle swarm optimization which is capable of achieving global solutions is simple, excellent computationally efficiency and has better and stable dynamic convergence characteristics with a high probability.

Keywords: Economic Dispatch, Optimization techniques, Heuristic programming, Particle Swarm Optimization, multi-fuel option, Non-linear constraint

1. Introduction

The cost of electricity is increasing globally due to high cost of fossil fuel especially in countries where fossil fuels are not vastly deposited. In a competitive electricity market, to meet customers demand at the same time reducing the cost of generation becomes a major concern to generating company. To address this problem and save significant revenue, Economic dispatch which involves the allocation of power demand among generators in such a manner that will minimize the total fuel cost and maintain physical and operational constraint has been a hot area of research in recent time. It is one of the major challenge confronting power system operators which before now had been handled by conventional optimization algorithms such as Lamda iteration, quadratically constrained programming base point participation factor[1] gradient method, Newton method [2]. In the past, the cost function is approximated to be monotonically increasing in quadratic or piecewise-linear order[3]. This assumption is not valid because the cost functions of modern generators possess higher order of nonlinearities making the equations complex, non-convex with multiple minimal points resulting into serious challenge of locating global minimal[4]. The complexities and non-linearity is as a result of valve point loading[5], prohibited operating zones [6]and ramp rate limits of generators[7]etc. Conventional optimization methods are ineffective is to model this complexities introduced due to nonlinearities of the modern generators. To achieve a fast and near global optimal solution, meta-heuristic optimization techniques have been proposed in literatures. Meta-heuristic optimization such as evolutionary algorithm (e.g Genetic algorithm), physical-based algorithm (e.g Gravitational Local Search, Big-Bang Big-Crunch (BBBC) and swarm Intelligence (e.g

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particle Swarm Optimization, ant colony). Today, swarm intelligence is widely used in the field of optimization because of its ability to preserve information, save the best information in the memory, the ease of implementation[8]. These algorithms mostly mimic the social behavior of swarms, herds, flocks, or schools of creatures in nature. The commonest and widely used one is particle Swarm Optimization (PSO)[8]

Particle swarm optimization (PSO) is a population- based meta-heuristic optimization and it iteratively optimize a problem using the best function or quality. Each particle in the population is moved in the search space influenced by its local best known position until the best known position is achieved in the search space. Particle swarm optimization has been researched extensively in the area of economic dispatch. Due to its flexibility, robustness, simplicity, fast convergence, it has been widely accepted in solving economic dispatch problem.

The author in [9] proposed the use of PSO to minimize the cost function as a single objective function in 6-generating unit system while the author in [10], [11] used PSO to solve non- smooth cost function with equality and inequality constraint. Ref deployed the use of PSO to solved economic dispatch problem considering constraint such as such as ramp rate limits, prohibited operating zone, and non-smooth cost functions and ref [12] investigated the use of PSO in solving economic dispatch with multiple fuel option subject to power balance and operating limit constraints. This research consider the use of PSO in solving economic dispatch problem considering power balance limit, operating limit constraint and effect of line losses with multiple fuel option resulting into nonsmooth cost function. All the paper reviewed only considered nonsmooth cost function with assumption that the line losses are neglected. The practical economic dispatch problem does not follow this track but involves transmission line losses and other constraint. The rest of the chapter is organized as follow:

2. Literature review

2.1. Review of Economic Dispatch

Economic Dispatch (ED) is defined as the process of allocating total power demand among committed generating unit economically at the same time satisfying various constraints distributing available load to the generating units so as save cost. In static economic dispatch, the objective of the conventional economic dispatch problem is to minimize the total cost of thermal generating units while satisfying various constraints including power balance and generator power limits. In the economic dispatch problem with multiple fuel options, the piecewise quadratic function is used to represent the multiple fuels which are available for each generating units[13]. There have been many algorithms proposed for economic dispatch. These include:

- Merit Order Loading
- Range Elimination to save cost
- Binary Section
- Secant Section
- Graphical/Table Look-Up
- Convex Simplex
- Dantzig-Wolf Decomposition etc.[8]

The following are well-known examples of “intelligent” algorithms that use clever simplifications and methods to solve computationally complex problems.

- Swarm Intelligence
- Tabu Search
- Simulated Annealing
- Genetic Algorithms
- Artificial Neural Networks
- Support Vector Machines[8]

2.2. Review of Particle Swarm Optimization

Kennedy and Eberhart [6] developed a particle swarm optimization algorithm based on the behaviour of individuals (i.e., particles or agents) of a swarm. Its roots are in zoologist’s modelling of the movement of individuals within a group. It has been noticed that members of the group seem to share information among them, a fact that leads to increased

efficiency of the group [9]. The PSO algorithm searches in parallel using a group of particles. Each particle corresponds to a candidate solution to the problem. A particle moves toward the optimum based on its present velocity, its previous experience, and the experience of its neighbours. In an n -dimensional search space, the position and velocity of particle are represented as vectors $X_i = (x_{i1}, \dots, x_{in})$ and $V_i = (v_{i1}, \dots, v_{in})$, where the dimension represents the number of components. Let $Pbest_i = (x_{i1}^p, \dots, x_{in}^p)$ and $Gbest = (x_{i1}^g, \dots, x_{in}^g)$ be the best position of particle and its neighbour's best position so far, respectively. The modified velocity and position of each particle can be calculated as follows:

$$V_i^{k+1} = w \cdot V_i^k + c_1 \cdot rn_1 \cdot (Pbest_i^k - X_i^k) + c_2 \cdot rn_2 \cdot (Gbest^k - X_i^k) \quad (1)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2)$$

Where

- V_i^k Velocity of Particle i at iteration k ;
- w Inertia weight factor;
- c_1, c_2 Acceleration coefficient;
- rn_1, rn_2 Random number between 0 and 1;
- X_i^k Position of particle i at iteration k ;

The search mechanism of the PSO using the modified velocity and position of individual based on (1) and (2) is the figure below:

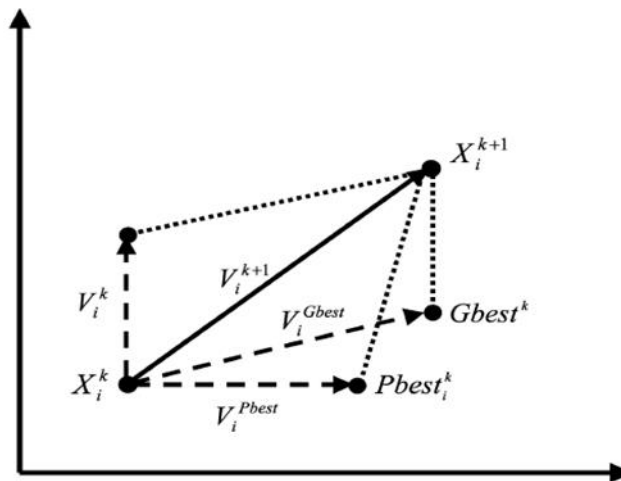


Figure 1: The search mechanism of the particle swarm optimization[14]

In this paper, the approach to implement the particle swarm optimization algorithm will be described in solving the economic dispatch problems. The process of the particle swarm optimization algorithm can be summarized as follows:

- Initialization of a group at random while satisfying constraints.
- Velocity and position updates while satisfying constraints.
- Update of $Pbest$ and $Gbest$.
- Activation of space reduction strategy.
- Go to Step 2 until satisfying stopping criteria.[10]

2.3. Initialization and Structure of Individuals

In the initialization process, a set of individuals is created at random. In this paper, the structure of an individual for economic dispatch problem is composed of a set of elements (i.e., generation outputs). Therefore, individual's position at iteration 0 can be represented as the vector of $X_i^0 = (x_{i1}^0, \dots, x_{in}^0)$ where n is the number of generators [10]

The velocity of individual i (i.e., $V_i^0 = (v_{i1}^0, \dots, v_{in}^0)$) corresponds to the generation update quantity covering all generators. The elements of position and velocity have the same dimension, i.e., MW in this case. Note that the

summation of all elements of individual i (i.e., $\sum_{j=1}^n P_{ij}^0$) should be equal to the total system demand P_D and the created element j of individual i at random (i.e., P_{ij}^0) should be located within its boundary. Although we can create element of individual at random satisfying the inequality constraint by mapping $[0, 1]$ into $[P_{jmin}, P_{jmax}]$, it is necessary to develop a new strategy to handle the equality constraint. To do this, the following procedure is suggested for any individual in a group:

Step 1) Set $j = 1$.

Step 2) Select an element (i.e., generator) of an individual at random.

Step 3) Create the value of the element (i.e., generation output) at random satisfying its inequality constraint.

Step 4) If $j = n - 1$ then go to Step 5; otherwise and $j = j + 1$ go to Step 2.

Step 5) the value of the last element of an individual is determined by subtracting $\sum_{j=1}^{n-1} P_{ij}^0$ from the total system demand, P_D . If the value is in the range of its operating region then go to Step 6; otherwise go to Step 1.

Step 6) Stop the initialization process. [10]

After creating the initial position of each individual, the velocity of each individual is also created at random. The following strategy is used in creating the initial velocity:

$$(P_{jmin} - \varepsilon) - P_{ij}^0 \leq v_{ij}^0 \leq (P_{jmax} + \varepsilon) - P_{ij}^0 \quad (3)$$

Where ε is a small positive real number. The velocity of element j of individual i is generated at random within the boundary. The developed initialization scheme always guarantees to produce individuals satisfying the constraints while maintaining the concept of the PSO algorithm. The initial $Pbest_i$ of individual i is set as the initial position of individual i and the initial $Gbest$ is determined as the position of an individual with minimum payoff of the objective function. [10].

2.4. Velocity Update

In the velocity updating process, the values of parameters such as w , c_1 , and c_2 should be determined in advance. The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward the $Pbest_i$ and $Gbest$ positions. Suitable selection of inertia weight can provide a balance between global exploration and local exploitation, and results in a lower number of iterations to find the optimal solution. In general, to enhance the convergence characteristics, the inertia weight factor w is designed to decrease linearly (i.e., Inertia Weight Approach (IWA) [11], [12], descending from w_{min} to w_{max} to as follows:

$$w^k = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times K \quad (4)$$

Where $iter_{max}$ corresponds to the maximum iteration number. Using the new position X_i^{k+1} , the $Pbest_i$ and $Gbest$ are updated at iteration $k+1$ using the greedy selection.

2.5. Position Modification Considering Constraints

The position of each individual is modified by

$$P_{ij}^{k+1} = \begin{cases} P_{ij}^k + V_{ij}^{k+1} & \text{if } P_{ij,min} \leq P_{ij}^k + V_{ij}^{k+1} \leq P_{ij,max} \\ P_{ij,min} & \text{if } P_{ij}^k + V_{ij}^{k+1} < P_{ij,min} \\ P_{ij,max} & \text{if } P_{ij}^k + V_{ij}^{k+1} > P_{ij,max} \end{cases} \quad (5)$$

Figure 2 Illustrates how the position of element j of individual i is adjusted to its maximum when the over-velocity situation occurs.

Although the aforementioned method always produces the position of each individual satisfying the inequality constraints of the generator operating limit ($P_{i,min} \leq P_i \leq P_{i,max}; i = 1, \dots, n$), the problem of equality constraint still remains to be resolved. Therefore, it is necessary to develop a new strategy such that the summation of all elements in an individual (i.e., $\sum_{j=1}^n P_{ij}^k$) is equal to the total system demand. [11]. [10]

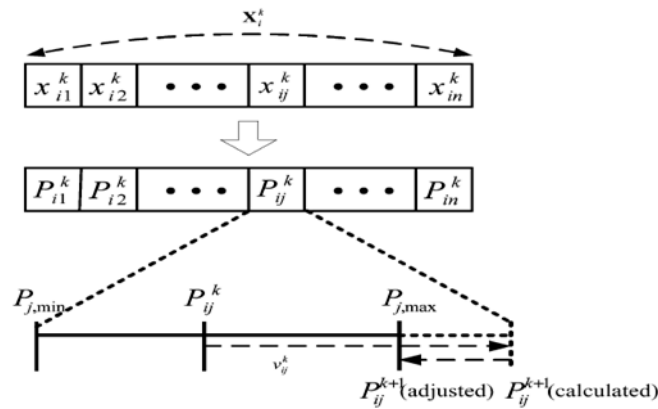


Figure 2 Adjustment strategy for an individual's position within boundary [10]

2.6. Update of Pbest and Gbest

The P_{best} of each individual at iteration $k+1$ is updated as follows:

$$P_{best}_i^{k+1} = X_i^{k+1} \text{ if } TC_i^{k+1} < TC_i^{k+1} \quad (6)$$

$$P_{best}_i^{k+1} = P_{best}_i^{k+1} \text{ if } TC_i^{k+1} \geq TC_i^{k+1} \quad (7)$$

Where

TC_i the object function evaluated at the position of individual i .

Additionally, G_{best} at iteration $k+1$ is set as the best evaluated position among $P_{best}_i^{k+1}$. [10].

2.7. Space Reduction Strategy

To accelerate the convergence speed to the solutions, the multiple particle swarm optimization has introduced the search space reduction strategy. This strategy is activated in the case when the performance is not increased during a pre-specified iteration period. In this case, the search space is dynamically adjusted (i.e., reduced) based on the "distance" between the G_{best} and the minimum and maximum output of generator j . To determine the adjusted minimum/maximum output of generator i at iteration k , the distance is multiplied by the predetermined step-size Δ and subtracted (added) from the maximum (minimum) output at iteration as described in (8 and 9)

$$P_{j,max}^{k+1} = P_{j,max}^k - (P_{j,max}^k - G_{best}_j^k) \times \Delta \quad (8)$$

$$P_{j,min}^{k+1} = P_{j,min}^k + (P_{j,min}^k - G_{best}_j^k) \times \Delta \quad (9)$$

Fig. 3 illustrates how the search space of each generator is dynamically reduced when activated.

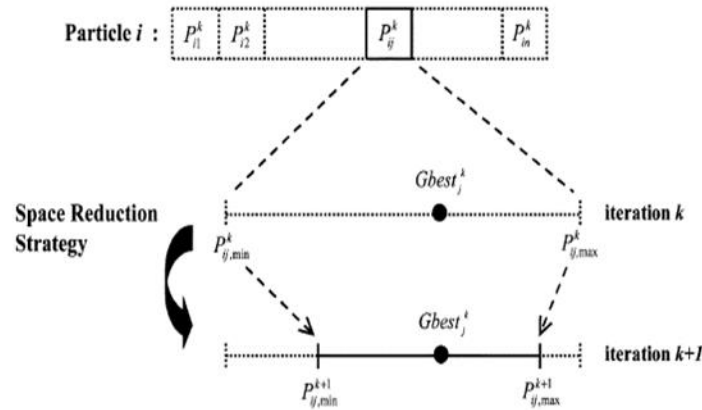


Figure 2 Schematic of the dynamic space reduction strategy[10].

2.8. Stopping Criteria

The multi-objective particle swarm optimization is terminated if the iteration approaches to the predefined maximum iteration. [10].

3. Methodology

3.1. Modelling of Economic Dispatch and Problem Formulation

The objective of the conventional economic dispatch problem is to minimize the total cost of thermal generating units while satisfying various constraints including power balance and generator power limits. In the economic dispatch problem with multiple fuel options, the piecewise quadratic function is used to represent the multiple fuels which are available for each generating units [13]. Therefore, the objective of the economic dispatch problem with multiple fuel options is to find a suitable fuel for each generating unit so as their total cost is minimized while satisfying different constraints including power balance and generation limits.

Mathematically, the problem is formulated as follows:

$$\text{Min } F = \sum_{i=1}^n F_i(P_i) \quad (14)$$

In general, a piecewise quadratic function is used to represent the input-output curve of a generator with multiple fuels and described as

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2, \text{Fuel 1 } P_{imin} \leq P_i \leq P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2, \text{Fuel 2 } P_{i1} \leq P_i \leq P_{i2} \\ \vdots \\ a_{ik} + b_{ik}P_i + c_{ik}P_i^2, \text{Fuel k } P_{ik-1} \leq P_i \leq P_{imax} \end{cases} \quad (15)$$

Where

- a_{ik}, b_{ik}, c_{ik} Cost Coefficient for unit i for fuel type k
- P_i Output power of unit i (MW)
- P_{imin}, P_{imax} Lower and Upper generation limits of unit i

Subject to

a) Power balance constraint

$$\sum_{i=1}^n P_i - P_L - P_D = 0 \tag{16}$$

Where the power loss is approximately calculated by Kron’s formula

$$P_L = \sum_{i=1}^N \sum_{j=1}^N P_i B_{ij} P_j + \sum_{i=1}^N B_{0i} P_i + B_{00} \tag{17}$$

b) Generator operating limits

$$P_{i,min} \leq P_i \leq P_{i,max}; i = 1, \dots, N \tag{18}$$

Where

- P_i Output power of unit i
- P_D Total load demand of the system (MW)
- P_L Total network loss of the system (MW)
- B_{ij}, B_{0i}, B_{00} Transmission loss formula coefficients

Table 1 Data for 3-Unit System

S/N	Generating Units	Lower Limit, P_{min} (MW)	Upper Limit, P_{max} (MW)	Cost Coefficient (a, b, c)
1	Generator 1	10	85	0.008, 7, 200
2	Generator 2	10	80	0.009, 6.3, 180
3	Generator 3	10	70	0.007, 6.8, 140

$$B_{if} = \begin{matrix} 0.000218 & 0.000093 & 0.000028 \\ 0.000093 & 0.000228 & 0.000017 \\ 0.000028 & 0.000031 & 0.000015 \end{matrix}$$

$$B_{0i} = 0.0003 \quad 0.0031 \quad 0.0015$$

$$B_{00} = 0.030523$$

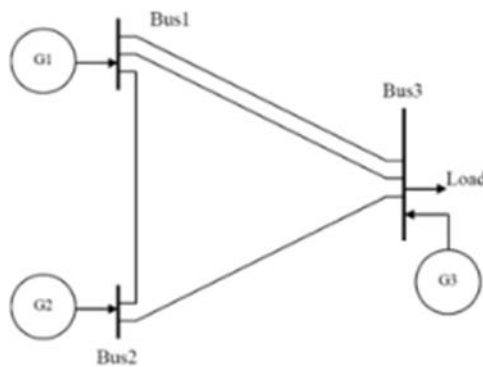


Figure 5 Typical 3-Unit system

Table 2 Data for 6-Unit System

Generating Unit	Lower Limit, P_{\min} (MW)	Upper Limit, P_{\max} (MW)	Cost Coefficient (a, b and c)
1	100	500	0.007, 7, 240
2	50	200	0.0095, 10, 200
3	80	300	0.009, 8.5, 300
4	50	150	0.008, 11, 200
5	50	200	0.008, 10.5, 220
6	50	120	0.0075, 12, 120

$$B_{ij} = \begin{matrix}
 \begin{matrix}
 0.000014 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\
 0.000017 & 0.000006 & 0.000013 & 0.000016 & 0.000015 & 0.000002 \\
 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\
 \\
 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000003 & 0.000025 \\
 0.000026 & 0.000015 & 0.000024 & 0.000003 & 0.000069 & 0.000032 \\
 0.000022 & 0.000002 & 0.000019 & 0.000025 & 0.000032 & 0.000085
 \end{matrix} \\
 \\ \\
 \begin{matrix}
 B_{0i} = 0 \\
 B_{00} = 0
 \end{matrix}
 \end{matrix}$$

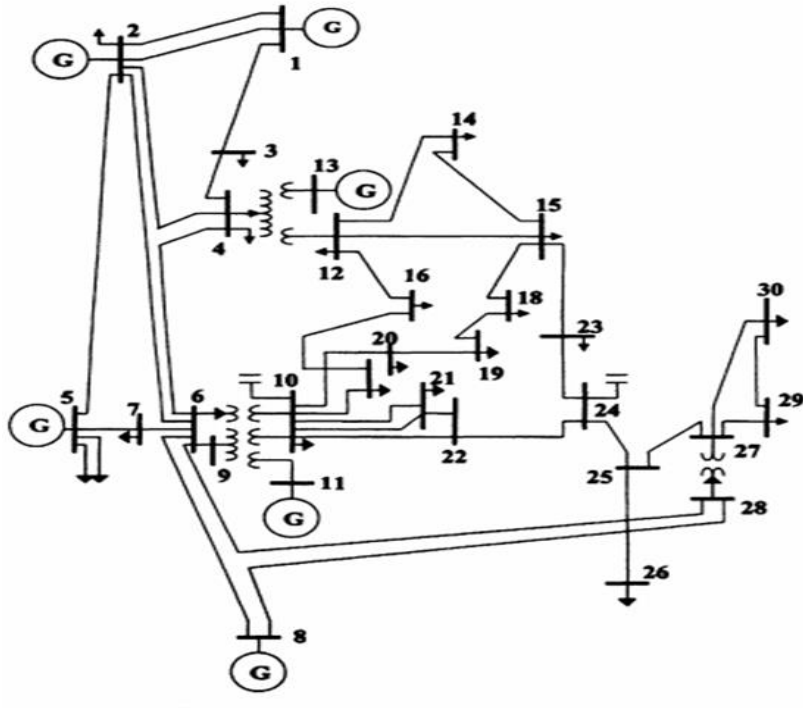


Figure 3 Typical 6-Unit system

4. Results

4.1. Test Strategy

To verify the feasibility and effectiveness of Particle Swarm Optimization (PSO) in solving economic dispatch, the heuristic algorithms was applied to

- 3-unit system with transmission losses
- 3-unit system without transmission losses
- 6-unit system with transmission losses
- 6-unit system without transmission losses
- 3-unit system with multiple fuel options

The economic dispatch problem was solved using particle swarm optimization and the performance of each generator has been judged using MATLAB 8.1.0 on an Intel(R) Pentium(R) N3540 processor, 2.16GHz with 4GB RAM.

4.2. Parameter Determination Strategy

The several parameters to be determined for the implementation of the particle swarm optimization such as w , c_1 and c_2 in . In this journal, these parameters have been determined and to avoid the problem of the curse of dimensionality, the procedures and strategies are determined as follows:

1. The values of c_1 and c_2 have the same value, which implies the same weights are given between Pbest and Gbest in the evolution processes.
2. The values of w are varied from 0.9 to 0.4

The parameters of the PSO are as follows

- Population size is 50
- Number of generation is 500

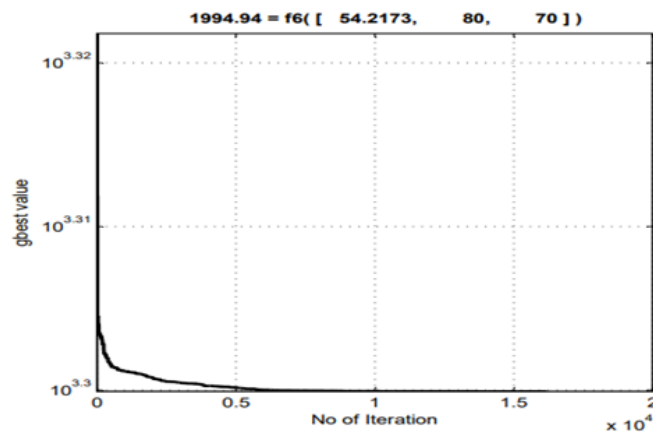


Figure 4 Convergence Characteristics of PSO for 3-unit system

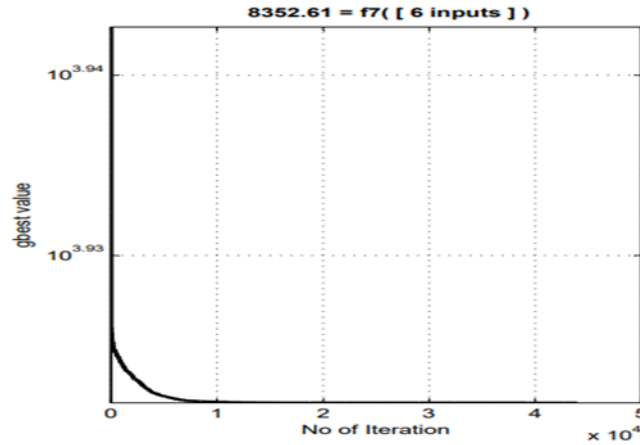


Figure 5 Convergence Characteristics of PSO for 6-unit system

4.3. Solution Quality

The particle swarm optimization was tested to know its effectiveness in minimizing generation cost and as well meeting the various load demands. The first test system has three-generating units and the parameters of the 3-Unit system has transmission loss coefficient represented in B-matrix form as shown in table 1. The output of the particle swarm optimization are presented in table 3. At various load demand (with 10MW increment), the result is given by particle swarm optimization algorithm in term of generation cost and power loss minimization.

Table 3 Results by particle swarm optimization at different load values.

Power Demanded (MW)	Gen 1 (MW)	Gen 2 (MW)	Gen 3 (MW)	Total Cost (#/hr.)	Power Loss (MW)
100	16.64	49.69	34.78	1219	1.08
110	19.70	52.90	38.72	1293	1.30
120	23.26	55.73	42.56	1368	1.53
130	26.30	58.78	46.73	1444	1.78
140	29.72	61.40	50.96	1521	2.05
150	32.74	64.82	54.82	1598	2.35
160	36.03	67.42	59.24	1676	2.65
170	39.37	70.50	63.15	1754	2.99
180	43.00	73.28	67.09	1834	3.35
190	46.88	76.90	70.00	1914	3.74
200	54.22	80.00	70.00	1995	4.19
210	64.69	80.00	70.00	2078	4.65
220	75.20	80.00	70.00	2164	5.17

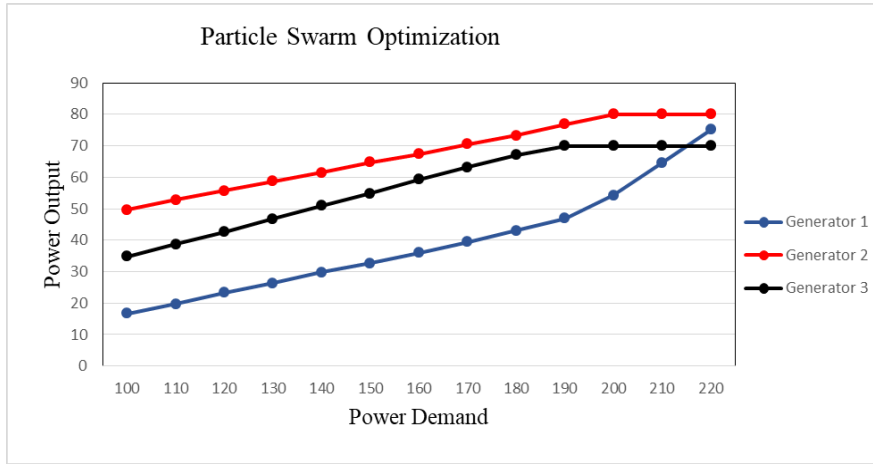


Figure 6 Power Output of three generators using Particle Swarm Optimization

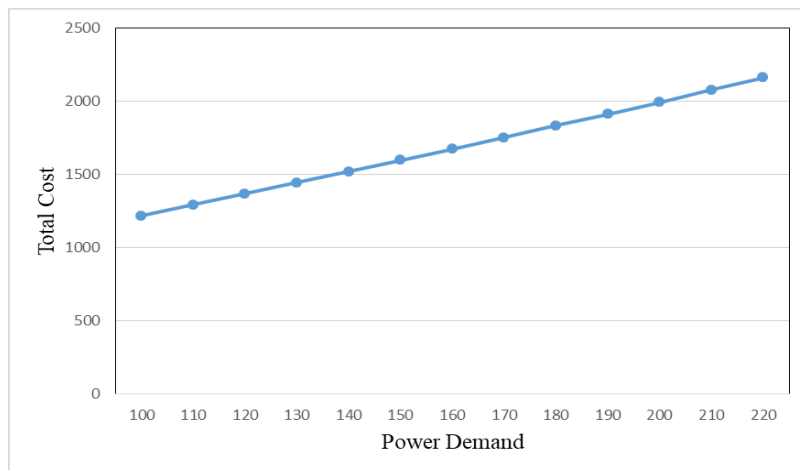


Figure 7 Total Cost using Particle Swarm Optimization

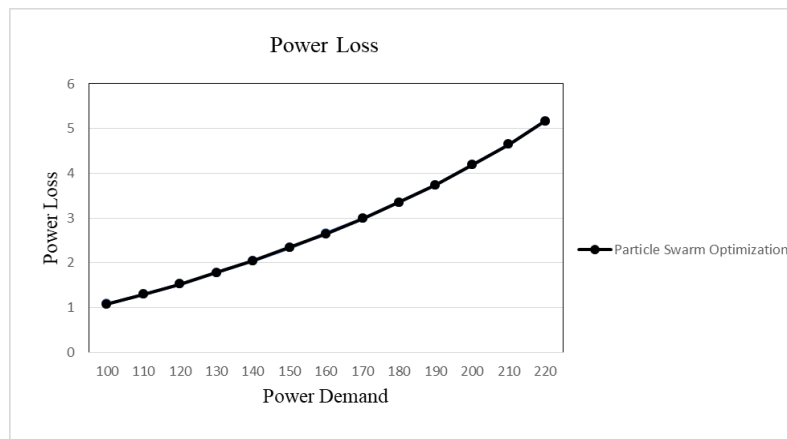


Figure 8 Total Power loss for three generators

Considering the same 3-Unit system without transmission losses (from Table 1), it is found that the global solution of particle swarm optimization has a very high probability as shown in Table 4, exactly satisfying the equality and

inequality constraints. Although particle swarm optimization and genetic algorithm have different load sharing for different load demand, the cost of generation remain the same for various load demands.

Table 4 Results by particle swarm optimization without transmission loss at different load values.

Power Demanded (MW)	Gen 1 (MW)	Gen 2 (MW)	Gen 3 (MW)	Total Cost (#/hr.)
100	15.83	52.21	31.96	1211
110	18.65	55.54	35.81	1283
120	22.23	58.54	39.23	1357
130	25.32	61.07	43.61	1431
140	28.90	64.15	46.96	1505
150	32.11	67.23	50.67	1580
160	35.25	70.36	54.39	1655
170	38.59	73.11	58.30	1731
180	41.93	75.92	62.15	1807
190	45.13	78.92	65.95	1884
200	50	80	70	1962
210	60	80	70	2041
220	70	80	70	2121

Increasing the number of generating units to six and using particle swarm optimization to solve the economic dispatch problem of the 6-unit system, Table 2 shows the parameters of the 6-Unit system with their cost coefficient. The solution is shown in table 5.

Table 5 Result by particle swarm optimization with transmission loss at different load values.

Power Demanded (MW)	Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Unit 4 (MW)	Unit 5 (MW)	Unit 6 (MW)	Total Cost (#/hr.)	Power Loss (MW)
500	221.08	50	84.51	50	50	50	6132	5.59
600	280.64	50	127.28	50	50	50	7203	7.92
700	323.55	76.75	158.49	50	51.94	50	8353	10.74
800	355.82	99.22	181.90	50	77.41	50	9559	14.34
900	383.07	118.31	201.36	67.35	98.41	50	10813	18.51
1000	410.60	137.35	220.62	86.15	118.52	50	12110	23.23
1100	425.99	155.27	238.95	104.26	138.30	65.83	13452	28.60
1200	459.43	171.32	255.41	120	154.43	74.02	14835	34.60
1300	482.90	187.66	272.32	135.38	171.68	91.31	16257	41.26
1400	500	200	292.37	150	192.54	113.95	17720	48.61

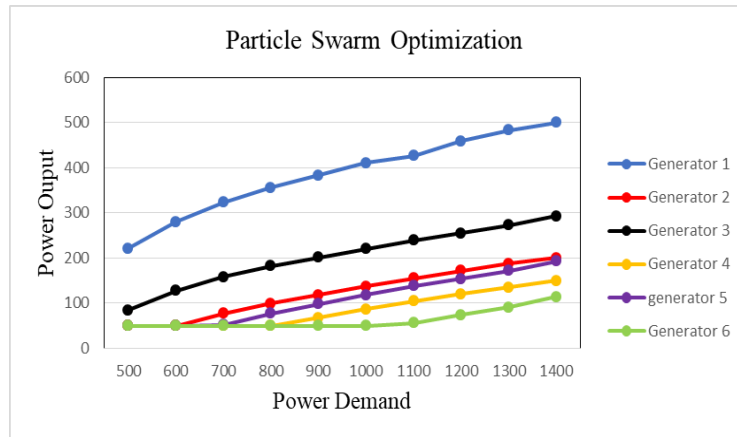


Figure 9 Power output of six generators using Particle Swarm Optimization

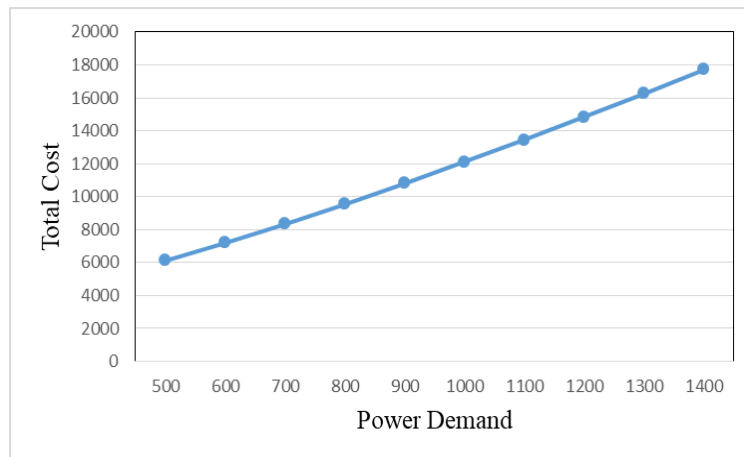


Figure 10 Total cost of generation using Particle Swarm Optimization

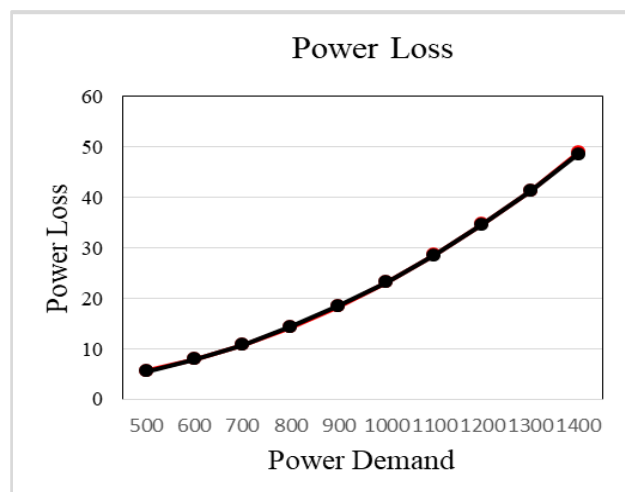


Figure 11 Total Power loss for six generators

Again, the particle swarm optimization gives a slightly different solution for 6-unit system without transmission loss. The solution provided by the particle swarm optimization in terms of generation cost and transmission loss is shown in table 6.

Table 6 Result by particle swarm optimization without transmission loss at different load values.

Power Demanded (MW)	Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Unit 4 (MW)	Unit 5 (MW)	Unit 6 (MW)	Total Cost (#/hr.)
500	215.51	50	84.49	50	50	50	6076
600	271.66	50	128.34	50	50	50	7117
700	312.97	72.47	158.81	50	54.76	50	8229
800	341.88	94.26	182.53	50	81.34	50	9388
900	367.35	112.84	202.64	63.75	103.43	50	10585
1000	391.34	130.63	221.52	82.50	124	50	11817
1100	414.53	147.84	239.05	100.5	143.93	54.16	13082
1200	435.14	161.92	253.65	115.64	161.07	72.58	14376
1300	453.85	176.30	270.28	130.65	178.18	90.73	15698
1400	473.66	191.32	285.13	145.86	195.70	108.32	17047

An economic dispatch problem with multiple fuel options has also been considered. Particle swarm optimization was applied to solve the problem. The parameters of the generating unit as shown in table 7. The results of the three approaches with multiple fuel option combination are shown in table 8a-8d.

Table 7 Data of 3-unit generator with multiple fuel options.

Generating Unit	Lower limit, P_{\min}	Upper Limit, P_{\max}	FT	a	B	c
1	190	490	1	0.001066	0.8773	13.92
			2	0.001597	-0.5206	99.76
2	85	265	1	0.002758	-0.6348	52.85
			2	0.001049	0.03114	1.983
3	200	500	1	0.0002454	0.3559	43.35
			2	0.001165	-0.2267	43.77

Table 8a Comparison of optimization method (Demand =700MW).

Unit	FT	Particle swarm optimization
1	1	190
2	1	207
3	1	303
Total Power		700
Total Cost		432.43

Table 8b Comparison of optimization method (Demand =700MW) with $FT_{unit3}=2$

Unit	FT	Particle swarm optimization
1	1	190
2	1	203.87
3	2	306.13
Total Power		700
Total Cost		340.70

Table 8c Comparison of optimization method (Demand =700MW) with $FT_{unit2,3}=2$

Unit	FT	Particle swarm optimization
1	1	190
2	2	148.34
3	2	361.66
Total Power		700
Total Cost		404.51

5. Conclusion

The complex problem of economic power dispatch is solved using particle swarm optimization. The test results clearly demonstrated that particle swarm optimization which is capable of achieving global solutions is simple, computationally efficient and has better and stable dynamic convergence characteristics. For the economic problem for 6-generator system, the particle swarm optimization has also provided the global solution with a high probability. In the case economic dispatch problem with multiple fuel option, the particle swarm optimization has good solution.

However, more research should be done on the effect of changing parameters of particle swarm optimization in solving economic dispatch problem. The parameters should be varied in other to see the behaviour of particle swarm optimization.

Compliance with ethical standards

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Disclosure of conflict of interest

There are no conflict of interest among the authors

References

- [1] A. J. Wood, B. F. Wollenberg, eacute Shebl&, and Gerald B, 'Power Generation, Operation and Control', p. 658.
- [2] M. E. El-Hawary and G. S. Christensen, *Optimal economic operation of electric power systems*. New York: Academic Press, 1979.
- [3] J. Zhu, *Optimization of Power System Operation*. 2015. doi: 10.1002/9780470466971.

- [4] K. T. Chaturvedi, M. Pandit, and L. Srivastava, 'Self-Organizing Hierarchical Particle Swarm Optimization for Nonconvex Economic Dispatch', *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1079–1087, 2008, doi: 10.1109/TPWRS.2008.926455.
- [5] D. C. Walters and G. B. Sheble, 'Genetic algorithm solution of economic dispatch with valve point loading', *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1325–1332, 1993, doi: 10.1109/59.260861.
- [6] S. O. Orero and M. R. Irving, 'Economic dispatch of generators with prohibited operating zones: a genetic algorithm approach', *IEE Proc. - Gener. Transm. Distrib.*, vol. 143, no. 6, pp. 529–534, 1996, doi: 10.1049/ip-gtd:19960626.
- [7] C. Wang and S. M. Shahidehpour, 'Effects of ramp-rate limits on unit commitment and economic dispatch', *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1341–1350, 1993, doi: 10.1109/59.260859.
- [8] S. Mirjalili, S. M. Mirjalili, and A. Lewis, 'Grey Wolf Optimizer', *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007.
- [9] A. Jaini, I. Musirin, N. Aminudin, M. M. Othman, and T. K. A. Rahman, 'Particle swarm optimization (PSO) technique in economic power dispatch problems', in *2010 4th International Power Engineering and Optimization Conference (PEOCO)*, Jun. 2010, pp. 308–312. doi: 10.1109/PEOCO.2010.5559236.
- [10] J.-B. Park, K.-S. Lee, J.-R. Shin, and K. Y. Lee, 'A Particle Swarm Optimization for Economic Dispatch With Nonsmooth Cost Functions', *Power Syst. IEEE Trans. On*, vol. 20, pp. 34–42, Mar. 2005, doi: 10.1109/TPWRS.2004.831275.
- [11] Zue-Lee Gaing, 'Particle swarm optimization to solving the economic dispatch considering the generator constraints', *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1187–1195, Aug. 2003, doi: 10.1109/TPWRS.2003.814889.
- [12] P. Sriyanyong *et al.*, 'An Approach to Economic Dispatch with Multiple Fuels Based on Particle Swarm Optimization', Toyama City, (Japan), 2011, pp. 327–336. doi: 10.1063/1.3596657.
- [13] M. K. Modi, A. Swarnkar, N. Gupta, K. R. Niazi, and R. C. Bansal, 'Stochastic Economic Load Dispatch with Multiple Fuels using Improved Particle Swarm Optimization', *IFAC-Pap.*, vol. 48, no. 30, pp. 490–494, 2015, doi: <https://doi.org/10.1016/j.ifacol.2015.12.427>.
- [14] Jong-Bae Park, Ki-Song Lee, Joong-Rin Shin, and K. Y. Lee, 'A particle swarm optimization for economic dispatch with nonsmooth cost functions', *IEEE Trans. Power Syst.*, vol. 20, no. 1, pp. 34–42, Feb. 2005, doi: 10.1109/TPWRS.2004.831275.