ECONOMIC LOAD DISPATCH IN POWER SYSTEM USING PSO

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By

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Dedicated to my Mata Rani, Bholenath and my beloved parents

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CERTIFICATE

This is to certify that the Thesis Report entitled "**ECONOMIC LOAD DISPATCH IN POWER SYSTEM USING PSO",** submitted by Mr. BHEESHM NARAYAN PRASAD bearing roll no. 212EE4219 in partial fulfillment of the requirements for the award of Master of Technology in Electrical Engineering with specialization in "Power Electronics and Drives" during session 2012-2014 at National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university/institute for the award of any Degree or Diploma.

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ABSTRACT

The economic load dispatch is an integral part of power system. The leading purpose is to minimize the fuel cost of power plant without violating any system constraints. Many conventional methods are applied to elucidate economic load dispatch through mathematical programming and optimization technique. The popular traditional method is the lambda-iteration method**.** Many heuristic approaches applied to the ELD problems such as dynamic programming, evolutionary programming, genetic algorithm, artificial intelligence, particle swarm optimization etc.

In this study, two cases are taken named as three unit system and six unit system. The fuel cost for both systems compared using conventional lambda-iteration method and PSO method. These calculations are done for without transmission losses as well as with transmission losses. In the end, the fuel cost for both methods compared to analyze the better one from them. All the analyses are executed in MATLAB environment.

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CHAPTER-1

1.1 INTRODUCTION

In power system, the economic load dispatch problem introduced when two or more generating units together produced the electrical power which exceeded the required generation. Engineers resolved this problem by implementing that how to divide the load among the committed generators. In reality, power plants are not situated near the load centres. Due to this, there is a change in fuel costs. If the generating system is in the normal operating condition, the generation would be more than power demand and losses. To cope up this, many methods of scheduling are employed. The modern power systems are the network of interconnections. In this interconnected system, the main task is to allocate the load demand among participating generators at minimum possible cost with satisfying all the system constraints. Thus, this is termed as economic load dispatch in power system.

Many conventional methods applied to solve ELD problems through mathematical programming and optimization techniques. The main conventional methods are the lambda iteration method [4], base point and participation factor method [4], gradient method [4] etc. From all these methods, the lambda iteration method uses frequently and this can be applied easily also. All these above mentioned methods can only feasible for linear cost approximation. The practical power system has discontinuities and nonlinearities due to prohibited operating zones [5], ramp rate limits [23], valve-point loading [11], and multi fuel options. Due to these nonlinearities the practical ELD becomes a complicated and non-convex optimization problem which has complex characteristics as well as non-convex characteristics. This ELD have multiple minima and it is very difficult to find global minima. In this case, the traditional methods fail to optimize.

Many heuristic approaches applied to the ELD problems such as dynamic programming, evolutionary programming, genetic algorithm, artificial intelligence, tabu search, particle swarm optimization. EP is a robust approach but in some cases it converges slowly near optimum. TS and SA are also robust approach to solve complex optimization problem.SA is time taking approach while TS is hard to explain the memory structure. DE is also a robust approach but its evaluating process is terminated at local optima. Thus DE cannot perform as per expectation. GA is a type of probalistic heuristic algorithm. GA is better than SA because of parallel search technique in GA. GA uses as one of the main algorithms to solve the ELD problems because of its performance for global optimization.

The introduction of Particle Swarm Optimization (PSO) was given by James Kennedy and Russell Eberhart .It optimizes the nonlinear function. It was inspired by the helping nature of particle (birds, fishes) while searching for food. This social system was stimulated for the development of this approach. PSO approach produces high-quality solution in small time and fast convergence.

In this study, two cases are taken named three unit system and six unit system. The fuel cost for both systems compared using conventional lambda-iteration method and PSO method. These calculations are done for without transmission loss as well as with transmission losses. In the end, the fuel cost for both methods compared to analyze the better one from them. All the analyses are executed in MATLAB environment.

1.2 Research Motivation

Revenue loss is an enormous concern for every nation. If this loss can be converted into the utilization then it will be substantial advantage for the nation. Adding to this, society wants secure electricity at minimum price with pollution at the least possible level in environment. In response of this task, many engineers put their ideas to reduce the fuel cost and pollution as well. In India, the total generation of electricity is 963.8 billion of electricity in the 2013-14. In this generation, thermal power plants responsible for 80-85% of total power generation. Interestingly, this ELD issue draws more attention.

1.3 Literature Review

Ching –Tzong Su and Chien-Tung Lin [6] used Hopfield method rather than sigmoidal neuron approach to estimate the ELD. Hopfield method employed here using the linear neuron model. This proposed method has the property of mutual coupling network along with nonhierarchical structure. This model does not need any kind of training like other neural network. Authors applied linear input-output model rather than sigmoidal neuron model in order to overcome the drawbacks (Drawbacks due to application of sigmoidal model). Here authors took two examples. The results of this approach show that this proposed method is more better and beneficial than the lambda-iteration method.

In large scale, Po-Hung and Hong-Chan Chang [7] employed genetic algorithm to evaluate ELD. Using Genetic algorithm in large-scale dispatch is very efficient. The solution time in this approach is increased with number of units. It can be taken as that algorithm which can be used worldwide. Due to the flexibility of genetic algorithm, this particular approach can deal with the prohibited zone, ramp rate limits and network losses. Therefore this approach is more practical. Authors proved that this proposed approach is better than lambda-iteration method especially in large-scale system.

In this paper, J.H.Park, Y.S. Kin, I.K.Eong and K.Y.Lee [8] proposed Hopfield neural network method. This method solved ELD problem with the help of piecewise quadratic cost function. In this paper, cost function is represented in the form of piecewise quadratic function instead of one convex function. Hopfield model is basically nonhierarchical structure and mutual coupling neural network. Authors took three cases to evaluate ELD through this method. When large numbers of generators are implemented then Hopfield neural network method can be used. The application of hardware can be favorable here due to the benefit of real time response.

D. O. Dike, M. I. Adintono, G. Ogu [9] investigated in practical aspect, the generation of power more than the load demand plus total losses. This very situation arises in the case of normal operating conditions. Here comes a method which taken for optimal dispatch. This proposed method used with the help of MATLAB. Damian Obioma Dike, Moses Izuchukwk Adintono and George Ogu took two cases and examined it with the numerical values that stated earlier. This all is done by considering the equal incremental cost.

A. Zareki and Md. F. B. Othman [10] proposed new evolutionary based approach named particle swarm optimization (PSO) to evaluate ELD. This method gave all the values of generation of power by each generator. Authors used piecewise quadratic function to indicate the cost of fuel equation of the each generating units. The transmission losses are represented by B-coefficients matrix. There are four case are taken here. The results of these cases are compared with the Genetic Algorithm (GA) and Quadratic programming (QR) base approaches. The results revealed that the PSO has the property of higher quality solution with simplicity in calculation and fast convergence.

In this study, A. Bhattacharya and P. K. Chattopdhyay [11] took the composition of differential evolution along with biogeography-based optimization. This DE/BBO algorithm is applied for convex ELD problem as well as non-convex ELD problems. This algorithm took the consideration of prohibited zones, valve-point loading, ramp rate limits and transmission losses. DE is very efficient and fast evolutionary algorithm while Biogeography-based optimization (BBO) is new optimization. Differential algorithm (DE) is one of the evolutionary algorithms which are population based algorithm. It deals with the non-linear, multi modal objective function and non-differential function. It has three operator named mutation, crossover and selection. Biogeography says; in which way species go from one place to another, in which way new species emerge and in which way species died out. In this paper, authors combined DE and BBO. They used their benefit in the form of improving the solution quality and convergence speed. Authors took four cases to demonstrate the efficiency of DE/BBO algorithm and they found that solution quality is better. The computational efficiency and robustness improved in this case also. The shortcoming of premature convergence is also avoided by the DE/BBO algorithm. In this totality, the DE/BBO method can be used in future.

K.T.Chaturvedi, M. Pandit, L. Srivastava [12] knew that particle swarm optimization is applied to ELD. This PSO works superior for problem of no convexity assumption. But this method converges prematurely for the case of multimodal problems. In this study, K.T.Chaturvedi, Manjaree Pandit and Laxmi Srivastava proposed self-organizing hierarchical particle optimization (SOH-PSO) to cope with the difficulty of premature convergence. Authors applied this SOH-PSO to the non-convex economic dispatch (NCED). When time-varying acceleration coefficients are introduced then the performance improved. Authors compared the result of this method with the result of other PSO algorithms. It revealed that SOH-PSO had better performance in the terms of stability, computational quality, solution quality, robustness and dynamic convergence.

In this paper, K. Meng, H. G. Wang, Z. Y. Dong and Kit Po Wong [13] proposed quantum-inspired particle swarm optimization (QPSO). Due to the application of quantum computing theory with implementation of chaotic sequence mutation and self-adaptive probability selection, QPSO having quicker convergence speed and better search ability. Ke Meng, Hong, Gang Wang, Zhao Yang Dong and Kit Po Wong compared it with particle swarm optimization (PSO), immune algorithm (IA), genetic algorithm (GA) and evolutionary programming (EP). Authors took three cases of three units, thirteen units and forty units. The results analysis showed that QPSO gave better performance as compared to others.

T. A. Albert Victoire, A. E. Jeyakumar [14] took the combination of Particle swarm optimization (PSO) and sequential quadratic programming (SQP) took to evaluate ELD. Here PSO is used as main optimizer while SQP is used to adjust the every refinement in the particular solution of PSO supervises. SQP is nonlinear programming method which is applied to constrained optimization. It is nearly similar to Newton's method. It performed well regarding accuracy, efficiency and successful solutions in large number of problems. Authors took three examples for this and concluded that convergence property is not strained which depends on the structure of incremental fuel cost function. PSO-SQP has the property of high quality solution and fast converging characteristic. This proposed method can also employ in prohibited zone, transmission losses and valve-point effect. In this way, this is more practical also.

In this paper, authors Yi Da, and G. Xiurun [15] used simulated annealing (SA) to modify PSO. The emergence of SAPSO-based ANN is done. In this study, the use of three-layer feed forward neural network is taken. This very neural network got trained like other models of neural networks. The three-layer feed forward neural network contains a hidden layer, an input layer and an output layer also. Authors analyzed that SAPSO-based ANN is better than PSO-based ANN. Due to its flexibility; it may be taken for other problems also.

Zee-Lee Gaing [17] proposed particle swarm (PSO) method to estimate ELD. As in practical views, the nonlinear characteristics (prohibited operating zone, ramp rate limits, on smooth cost function) of generating units are also considered. There were three cases taken to check the feasibility of PSO. The experimental result revealed that PSO is surpassing than GA. Other dominating properties of PSO are computational efficiency, solution quality and convergence characteristics.

B.K.Panigrahi, V.Ravikumar Pandi, S. Das [21] knew that in practical economic load dispatch have many kinds of constraints such as transmission losses, ramp rate limits, prohibited operating zones, valve point loading. In this paper, authors proposed adaptive-variable population-PSO technique for all these mentioned constraints. Authors took three cases (three unit system, 6 unit system and 15 unit system) and compared this result to GA, PSO. The comparison concluded that it is superior than earlier best obtained results. On the whole, it found that APSO can be used for smooth and non-smooth constraints in economic load dispatch problem as well. In practical, this method should be encouraged in future for large sized problem.

1.4 Thesis Organization

Chapter 2 illustrates the ELD in thermal power plant. It also emphasizes that why particularly thermal power plant is taken under consideration for ELD rather than nuclear power plant and hydro power plant. The discussions on the all-important system constraints are also done.

Chapter 3 explains the ELD by using traditional/conventional lambda-iteration method. This method is applied with transmission loss as well as without transmission loss. It describes the basic step to step procedure for this.

Chapter 4 firstly summarizes the PSO and then elaborates the ELD procedures neglecting transmission loss and considering transmission loss through PSO approach. It also outlines the flow chat of basic PSO.

Chapter 5 contains the two case study e.g. three unit system and six unit system. Both the cases are demonstrated through PSO and traditional/conventional lambda-iteration method. In the end, the fuel cost for both methods compared to analyze the better one from them. All the analyses are executed in MATLAB environment.

CHAPTER-2

ECONOMIC LOAD DISPATCH IN THERMAL POWER PLANT

Generator operating Cost

System Constraints

CHAPTER-2

2.1GENERATOR OPERATING COST

The sources of energy are diverse (coal, oil or gas, river water, marine tide, a radioactive matter, solar energy, wind energy). From these there are three types of generators are in use: nuclear, hydro and fossil (coal, oil or gas). Nuclear power plants are base-load power plants. Once it is on, it remains on and it supplies the base load. There is no running cost for hydro plant. Therefore, the costs of fossil plants come under the dispatch procedures. As there is inclusion of fuel cost, labour cost, maintenance and supplies for overall cost of operation. In general way, the labour cost, maintenance and supply not changed. Thus fuel cost taken into consideration. Figure shows the simple model of a fossil plant.

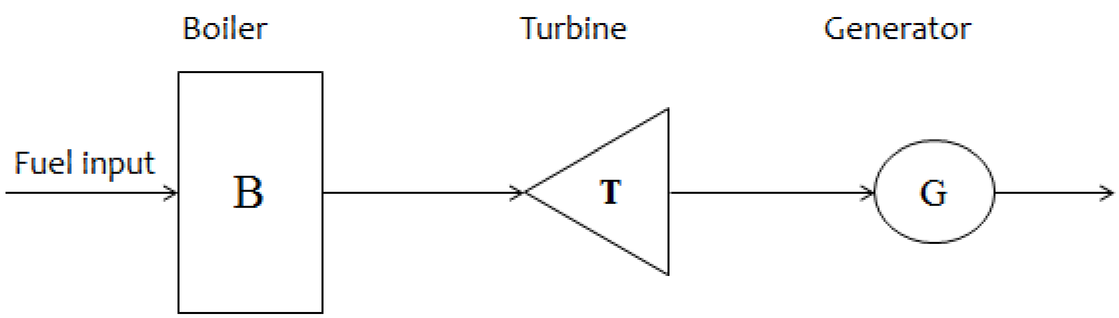


Fig 2.1: Model of fossil plant

In thermal plant, the input is taken in Btu/h while the output is taken in MW. In real cases, the formulation of fuel cost of generators is taken in the form of quadratic function of generated real power.

$$\mathrm{F}(P_{gi}) = a_i P^2{}_{gi} + b_i P_{gi} + c_i \ \text{ Rs/h} \tag{2.1}$$

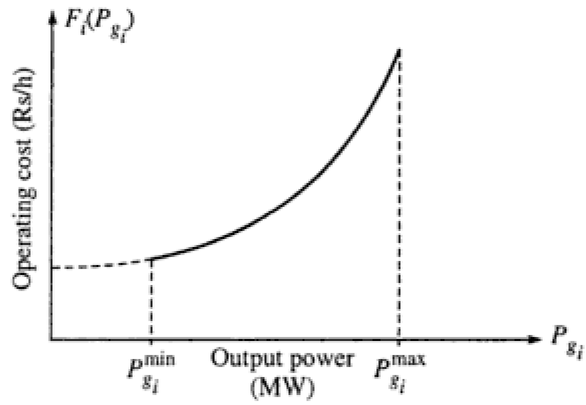


Fig 2.2: Operating cost curve

There are many discontinuities in fuel cost curve. These discontinuities exist due to use of extra boilers, steam condensers or other equipment. In power station, if the cost is representing by operation then discontinuities also exist. In the range of given continuity the incremental fuel cost expressed by a piece-wise linearization.

2.2 SYSTEM CONTRAINTS:

There are two types of system constraints

1. Equality Constraints
2. Inequality Constraints

Further inequality constraints are divided into two parts: (a) Hard type, (b) Soft type. Hard type are defined as the constraints which fall under the absolute and accurate category like the tapping range of an on-load tap changing transformer. Soft types are defined as the constraints which are flexible with them like the phase angles and nodal voltages between nodal voltages. By using penalty method, inequality constraints can be managed.

(a) Running Spare Capacity Constraints: Firstly this constraint should match with the two conditions (1) the load in unpredicted form in the system and (2) the forced outrage applied on alternators.

(b) Transmission Line Constraints: The thermal capability of the system restricts the flow of active and reactive power through the transmission line circuit. It is represented as

$$C_p \leq C_{p\ max}$$

Where $C_{p\ max}$ stands for maximum loading capacity of pth line

(c) Voltage Constraints: The values of voltages and phase angles at the different nodes have some restrictions. The values of voltage should be flexible under fixed limit. If this is not done then the system will become uneconomical.

$$|V_{p\ min}| \leq |V_p| \leq |V_{p\ max}|$$

$$\delta_{p\ min} \leq \delta_p \leq \delta_{p\ max}$$

(d) Transformer Tap Settings: The minimum tap setting is zero and maximum is one for auto-transformer i.e.

$$0 \leq t \leq 1.0$$

If tappings are given on the secondary side then relation for two winding transformer is as

$$0 \leq t \leq n$$

Where n stands for ratio of transformation.

(e) Generator Constraints: As the kVA loading of generator is $\sqrt{{P_p}^2 + {Q_q}^2}$ and value of this should not greater than C_p. This is due to the rise in temperature that follows ${P_p}^2 + {Q_q}^2 \leq {C_p}^2$.

The consideration is taken for real power generation as well as reactive power generation. The thermal factor is taken into account for the restriction of maximum real power production and the flame instability restricts the minimum real power production. Further it satisfies the given below relation

$$P_{p\ min} \leq P_p \leq P_{p\ max}$$

In the same way, the values of reactive power generation are considered. The field winding heating restricts the maximum reactive power stability limit of machine restricts the minimum reactive power. It follows this relation

$$Q_{p\,min} \leq Q_p \leq Q_{p\,max}$$

SUMMARY

It illustrates the ELD in thermal power plant. It also emphasizes that why particularly thermal power plant is taken under consideration for ELD rather than nuclear power plant and hydro power plant. The discussions of all important constraints are also done.

CHAPTER-3

ECONOMIC LOAD DISPATCH IMPLEMENTING LAMBDA ITERATION METHOD

Economic Dispatch Neglecting Loss

Economic Dispatch with Loss

Algorithm for ELD (Classical Method)

Algorithm for ELD Considering Limits (Classical Method)

CHAPTER-3

3.1ECONOMIC DISPATCH NEGLECTING LOSSES:

If there are NG generators are employed in a station and power demand P_D is given. The real power generation P_{gi} is to be assign in such a way that the total cost can be minimized. The optimization problem is expressed as

Minimize $\quad F(P_{gi}) = \sum_{i=1}^{NG} F_i(P_{gi}) \quad$ (3.1a)

Subject to

i. the energy balance equation

$$\sum_{i=1}^{NG}(P_{gi}) = P_D \tag{3.1b}$$

ii. the capacity constraints

$$P^{min}{}_{gi} \le P_{gi} \le P^{max}{}_{gi} \tag{3.1c}$$

(i=1, 2… NG)

Where

P_{gi} true power generation

P_D power demand

NG no. of plants

$P^{min}{}_{gi}$ lower-level limit of real power generation

$P^{min}{}_{gi}$ higher-level limit of real power generation

$F_i(P_{gi})$ is the running fuel cost of the i^{th} plant. It is formulated in the quadratic equation

$$F_i\left(P_{gi}\right) = a_i\, P^2{}_{gi} + b_i P_{gi} + c_i \text{ Rs/h} \tag{3.2}$$

A function can be minimized (or maximized) with the help of Lagrange multiplier. Using this method,

$$\text{L}\ (P_{gi}, \lambda) = F\left(P_{gi}\right) + \lambda\ (P_D - \sum_{i=1}^{NG} P_{gi}) \tag{3.3}$$

Where λ is the Lagrangian multiplier.

$P^*{}_{gi}$ is that the partial derivative of the Lagrange function stated by L= L (P_{gi}, λ) with respect to each of its arguments must be zero.

Applying the conditions to optimize the problem,

$$\frac{\partial L(P_{gi},\lambda)}{\partial P_{gi}} = \frac{\partial F\left(P_{gi}\right)}{\partial P_{gi}} - \lambda = 0 \quad (\text{i}=1,\ 2,\ldots,\text{NG}) \tag{3.4}$$

And

$$\frac{\partial L(P_{gi},\lambda)}{\partial \lambda} = P_D - \sum_{i=1}^{NG} P_{gi} = 0 \tag{3.5}$$

From equation (3.4)

$$\frac{\partial F(P_{gi})}{\partial P_{gi}} = \lambda \qquad (\text{i}=1,2,\ldots,\text{NG}) \tag{3.6}$$

Where $\frac{\partial F(P_{gi})}{\partial P_{gi}}$ is the incremental fuel cost of the i^{th} generator (Rs./MWh).

Equation (3.6) is known as coordination equation. From equation (3.2), the incremental cost can be stated as

$$\frac{\partial F(P_{gi})}{\partial P_{gi}} = 2a_i P_{gi} + b_i \tag{3.7}$$

Putting the incremental cost into eq (3.6), this equation becomes

$$2a_iP_{gi}+b_i \ = \lambda \qquad (i=1,2,...,NG) \tag{3.8}$$

Arranging Eq.

$$P_{gi} = \frac{\lambda - b_i}{2a_i} \qquad (i=1,2,...,NG) \tag{3.9}$$

Putting the value of P_{gi} in Eq. (3.5), we get

$$\sum_{i=1}^{NG} \frac{\lambda - b_i}{2a_i} = P_D$$

Or

$$\lambda = \frac{P_D + \sum_{i=1}^{NG} \frac{b_i}{2a_i}}{\sum_{i=1}^{NG} \frac{1}{2a_i}} \tag{3.10}$$

Therefore, the value of λ can be calculated using Eq. (3.10) and the value of P_{gi} can be calculated using Eq. (3.9).

3.2 ECONOMIC DISPATCH INCLUDING TRANSMISSION LOSSES

When long distance transmission of power is transmitted, the transmission losses come here. However it is important to consider this transmission in the policy of economic load dispatch.

In power system, the economic dispatch problem is termed as that which minimizes the total operating costs of a system simultaneously meeting the total load with transmission losses within generator limits.

Mathematically

Minimize

$$F(P_{gi}) = \sum_{i=1}^{NG} a_i \, P^2{}_{gi} + b_iP_{gi} + c_i \ \text{Rs/h} \tag{3.11a}$$

Subject to

i. the energy balance equation

$$\sum_{i=1}^{NG}(P_{gi}) = P_D + P_L \qquad (3.11b)$$

ii. the capacity constraints

$$P^{min}{}_{gi} \leq P_{gi} \leq P^{max}{}_{gi} \qquad (3.11c)$$

(i=1, 2… NG)

The way of representing transmission loss as a function of generators is through B-coefficients. The expression for loss formula through B-coefficient is

$$P_L = \sum_{i=1}^{NG}\sum_{i=1}^{NG} P_{gi}\, B_{ij} P_{gj} \text{ MW} \qquad (3.12)$$

Where,

P_{gi}, P_{gj}=real power generation at the i^{th} and j^{th} buses, respectively

B_{ij} = loss coefficients which cannot be changed in assumed conditions

NG= no. of plants.

The transmission loss formula of Eq. (3.12) is known as the George's formula.

Another precise form of transmission loss expression, defined as Kron's loss formula is

$$P_L = B_{00} + \sum_{i=1}^{NG} B_{i0}\, P_{gi} + \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_{gi}\, B_{ij} P_{gj} \text{ MW} \qquad (3.13)$$

Where

P_{gi}, P_{gj}= real power generation at the i^{th} and j^{th} buses, respectively

B_{00}, B_{i0} and B_{ij} are the loss coefficients which kept constant for certain conditions

NG is the no. of plants.

The above constrained optimization problem is converted into an unconstrained optimization problem. Using Lagrange multiplier,

$$L(P_{gi}, \lambda) = F(P_{gi}) + \lambda (P_D + P_L - \sum_{i=1}^{NG} P_{gi}) \qquad (3.14)$$

Where λ is Lagrangian multiplier.

Necessary condition for the optimization problem is

$$\frac{\partial L(P_{gi},\lambda)}{\partial P_{gi}} = \frac{\partial F(P_{gi})}{\partial P_{gi}} + \lambda \left(\frac{\partial P_L}{\partial P_{gi}} - 1\right) = 0 \qquad (i=1,2,\ldots,NG)$$

Arrange the equation,

$$\frac{\partial F(P_{gi})}{\partial P_{gi}} = \lambda \left(1 - \frac{\partial P_L}{\partial P_{gi}}\right) \quad (i= 1,2,\ldots,NG) \qquad (3.15)$$

Where

$\frac{\partial F(P_{gi})}{\partial P_{gi}}$ = incremental cost of the i^{th} generator (Rs/MWh)

$\frac{\partial P_L}{\partial P_{gi}}$ = incremental transmission losses.

This above equation is known as exact coordination equation.

Furthermore,

$$\frac{\partial L(P_{gi},\lambda)}{\partial \lambda} = P_D + P_L - \sum_{i=1}^{NG} P_{gi} = 0 \qquad (3.16)$$

By differentiating the transmission loss equation, eq. (3.13) with respect to P_{gi} ,

The incremental transmission loss can be obtained as

$$\frac{\partial P_L}{\partial P_{gi}} = B_{io} + \sum_{j=1}^{NG} 2B_{ij}\, P_{gj} \qquad (i=1,2,...,NG) \tag{3.17}$$

and by differentiating cost function eq. (3.13), with respect to P_{gi}, the incremental cost can be obtained as

$$\frac{\partial L(P_{gi})}{\partial P_{gi}} = 2a_i P_{gi} + b_i \qquad (i=1,2,..., NG) \tag{3.18}$$

Equation (3.15) can be formulated as

$$\frac{\frac{\partial F(P_{gi})}{\partial P_{gi}}}{1-\frac{\partial P_L}{\partial P_{gi}}} = \lambda$$

or
$$\left(\frac{\partial F(P_{gi})}{\partial P_{gi}}\right) L_i = \lambda \quad (i=1,2,...,NG) \tag{3.19}$$

Where $L_i = \frac{1}{1-\frac{\partial P_L}{\partial P_{gi}}}$ is termed as penalty factor of the i^{th} plant.

Substitute Eqs. (3.17) and (3.18) into Eq. (3.15)

$$2a_i P_{gi} + b_i = \lambda \left(1 - B_{io} - \sum_{j=1}^{NG} 2B_{ij}\, P_{gj}\right) \qquad (i=1, 2... NG)$$

Arrange this equation to obtainP_{gi},

$$2(a_i + \lambda B_{ii})\, P_{gi} = \lambda \left(1 - B_{io} - \sum_{j=1, j\neq i}^{NG} 2B_{ij}\, P_{gj}\right) - b_i \quad (i=1, 2... NG)$$

The value of P_{gi} can be formulated as

$$P_{gi} = \frac{\lambda\left(1 - B_{io} - \sum_{j=1, j\neq i}^{NG} 2B_{ij}\, P_{gj}\right) - b_i}{2(a_i + \lambda B_{ii})} \qquad (i=1, 2... NG) \tag{3.20}$$

3.3 Algorithm for ELD

1. Take given data, e.g. cost coefficients, a_i, b_i, c_i; B- coefficients,B_{ij},B_{i0},B_{00},(i= 1,2,...Ng; j = 1,2,..., NG); convergence tolerance, ε; step size ∝; and maximum iteration permitted, ITMAX, etc.

2. Evaluate the starting values of P_{gi} (i=1,2,…,NG) and λ by neglecting the transmission loss, i.e. P_L=0. Then the problem can be expressed by Eq. (3.1a) & (3.1b) and the solution can be simplified Eq.

$$\boldsymbol{\lambda} = \frac{P_D+\sum_{i=1}^{NG}\frac{b_i}{2a_i}}{\sum_{i=1}^{NG}\frac{1}{2a_i}} \quad \text{\& Eq.} \quad P_{gi} = \frac{\lambda-b_i}{2a_i} \quad \text{(i=1,2,…,NG)}$$

3. Set iteration counter, IT =1.

4. Evaluate P_{gi}(i=1,2,...,NG) using Eq

$$P_{gi} = \frac{\lambda\left(1-B_{i0}-\sum_{j=1}^{NG}2B_{ij}P_{gj}\right)-b_i}{2(a_i+\lambda B_{ii})} \qquad \text{(i=1, 2… NG)}$$

5. Evaluate transmission loss using Eq. (3.13).

6. Evaluate P = P_D + P_L - $\sum_{i=1}^{NG} P_{gi}$

7. Check | ΔP | ≤ ε, if 'yes', then TAKE Step 10.

Check IT ≥ ITMAX, if 'yes' then TAKE step 10.

8. Update λ^{new} = $\boldsymbol{\lambda}$ + α ΔP.

9. IT = IT + 1, = λ^{new} and GOTO Step 4 and repeat.

10. Evaluate optimal total cost from Eq. (3.11a) and transmission loss from Eq. (3.16).

11. Stop.

3.4 Algorithm for ELD considering limits

1. Take given data, e.g., cost coefficients, a_i, b_i, c_i; B- coefficients,B_{ij},B_{i0},B_{00},(i= 1,2,...NG; j = 1,2,..., NG); convergence tolerance, ε; step size ∝; and maximum iteration permitted, ITMAX, etc.
2. Evaluate the starting values of P_{gi} (i=1, 2... NG) and λ by neglecting the transmission losses i.e. P_L=0. Then the problem can be expressed by Eq. (3.1a) & (3.1b)

   $$\boldsymbol{\lambda} = \frac{P_D + \sum_{i=1}^{NG} \frac{b_i}{2a_i}}{\sum_{i=1}^{NG} \frac{1}{2a_i}} \quad \text{\& Eq.} \quad P_{gi} = \frac{\lambda - b_i}{2a_i} \quad (i=1,2,\ldots,NG)$$

3. Considering that no any generator is set at lower limit or upper limit.
4. Set iteration counter, IT =1.
5. Evaluate P_{gi}(i=1,2,…,R) using Eq

   $$P_{gi} = \frac{\lambda\left(1 - B_{i0} - \sum_{j=1}^{NG} 2B_{ij}P_{gj}\right) - b_i}{2(a_i + \lambda B_{ii})} \qquad (i=1,\ 2\ldots\ NG).$$

6. Evaluate transmission loss using Eq. (3.13).
7. Compute ΔP = P_D + P_L - $\sum_{i=1}^{NG} P_{gi}$
8. Check | ΔP | ≤ ε, if 'yes', then TAKE Step 11.

   Check IT ≥ ITMAX, if 'yes' then TAKE step 11.
9. Update λ^{new} = $\boldsymbol{\lambda}$ + α ΔP
10. IT = IT + 1, = λ^{new} and TAKE Step 5 and repeat.
11. Check the limits of generators, if no more violations then GOTO step 13, else fix as following.

    If $P_{gi} < P_{gi}^{min}$ then $P_{gi} = P_{gi}^{min}$

    If $P_{gi} > P_{gi}^{max}$ then $P_{gi} = P_{gi}^{max}$.
12. GOTO Step 4.
13. Compute the optimal load cost from Eq. (3.11a) and the transmission loss from Eq (3.13).
14. Stop.

SUMMARY

It explains the ELD by using traditional/conventional lambda-iteration method. This method is applied with transmission loss as well as without transmission loss. It describes the basic step to step procedure for this. There are two algorithm are provided namely ED (classical method) and ED considering limits (classical methods).

CHAPTER-4

PARTICLE SWARM OPTIMIZATION

Application of PSO in ELD

Flow Chart

ED without Transmission Loss through PSO

ED with Transmission Loss through PSO

CHAPTER 4

4.1 Application of PSO in ELD

The introduction of Particle Swarm Optimization (PSO) was given by James Kennedy and Russell Eberhart .It optimizes the nonlinear function. It was inspired by the helping nature of particle (birds, fishes) while searching for food. This social system was stimulated for the development of this approach. PSO approach produces high-quality solution in small time and fast convergence. In this process, particles fly in the space and search the food. They search the food by their own experience and also use the experience of nearby particles. Particles use the best position find by them along with their neighbour also. This social behaviour is taken as an optimization tool in soft computing.

- Let x represents position of particle.
- Let v represent velocity of particle
- The i^{th} particle is denoted as x_i = (x_{i1}, x_{i2},…, x_{id}) in the **d**-dimensional space.
- The best previous position of the i^{th} particle is noted and denoted as $pbest_i$ = ($pbest_{i1}$, $pbest_{i2}$,… $pbest_{id}$).
- The best among the Pbest is represented as $gbest_d$.
- For a particle, the description of rate of velocity is denoted as v_i = (v_{i1}, v_{i2},… v_{id})

The modified velocity and position of each particle can be derived using the present velocity and the distance from $pbest_{id}$ to $gbest_d$ as shown below

$$v_{id}^{(t+1)} = \omega.\ v_{id}^{(t)} + c_1 * \text{rand}()*(pbest_{id} - x_{id}^{(t)}) + c_2 * \text{Rand}()*(gbest_d - x_{id}^{(t)}) \quad (4.1)$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)},\ i = 1,2,\ldots n,\quad d = 1,2,\ldots m \quad (4.2)$$

Where

n = no. of particles in a group;   m = no. of members in a particle;

t= no.of iterations;   ω = inertia weight factor;

c_1, c_2 = acceleration constant;   rand (), Rand () = uniform random value in the range [0,1];

${v_i}^{(t)}$ = velocity of particle i at iteration t, ${x_i}^{(t)}$ = present position of particle i at iteration t

${V_d}^{min} \leq {v_{id}}^{(t)} \leq {V_d}^{max}$

In the upper section, V^{max} used to find the fitness or resolution. This is done for the space between the existing positions to the destination position. If the value of V^{max} goes high, the past good solution would be given by the particles. If the value of V^{max} goes lower, particle does not exceed over local solutions. In practical cases, the value of V^{max} is taken to b 10-20% of range of variable on each dimension.

The constants show the value of weighting of the stochastic acceleration. The task of this is to pull each other to approach the position of Pbest and Gbest. The low value of this sends the particles far from there. The high value describes sudden and expected movement towards the region in destination area. Thus, the values of c_1 and c_2 is taken 2.0 after numerous experimental experience.

The balanced value of inertia weight ω gives a balance for exploration in the local and global cases. In every case, the value of ω is taken 0.9 to 0.4 for one period as it decreases in linear manner.

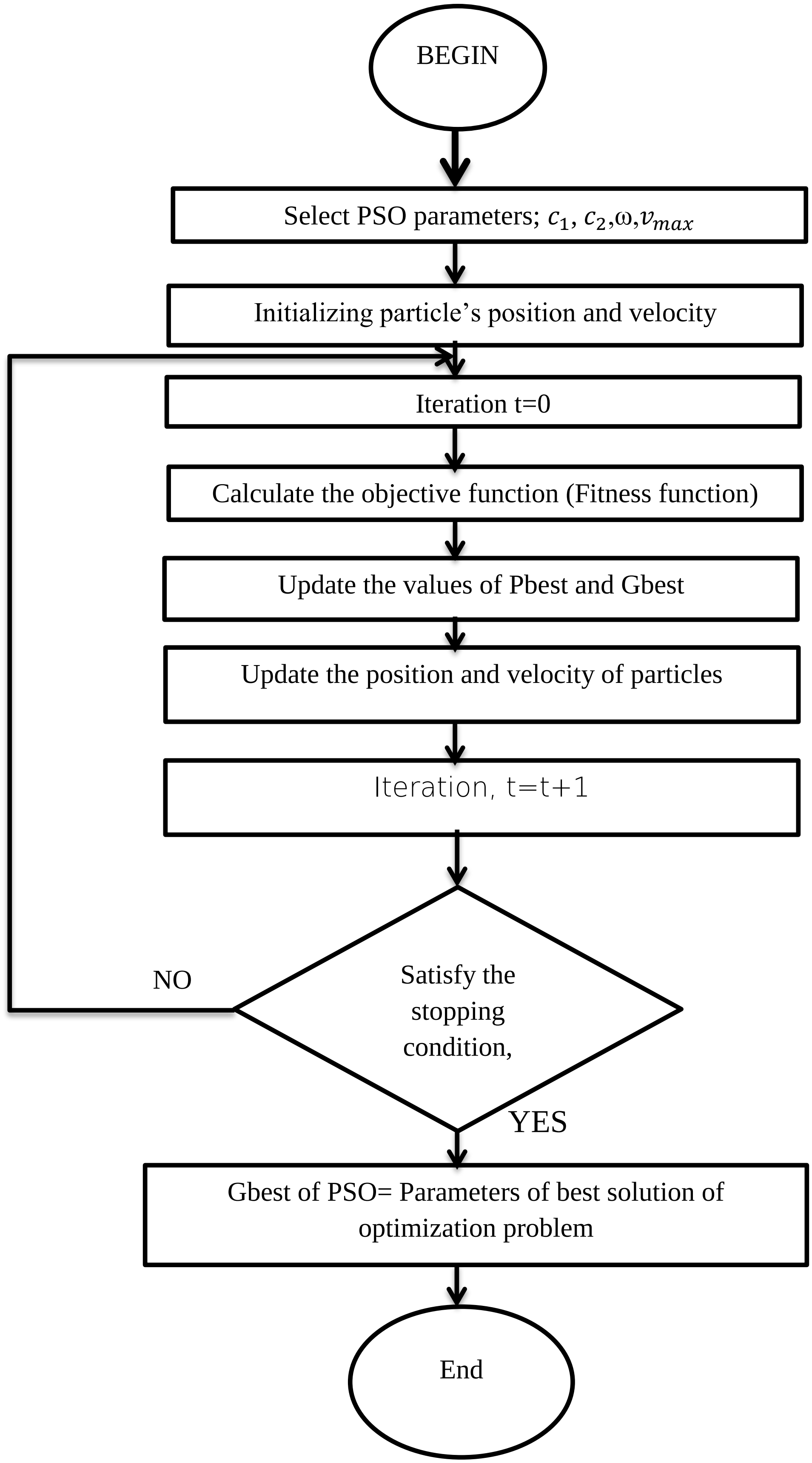
$$\omega = \omega_{max} - \frac{\omega_{max-}\omega_{min}}{iter_{max}} * \text{iter} \tag{4.3}$$

Where

$iter_{max}$ maximum no. of iterations

iter   present no. of iterations.

4.2Flow Chart



4.3 ED without Transmission Loss through PSO

Implementation

The main task of ED is to allocate the load demand among participating generators at minimum possible cost without violating any system constraints. The PSO can be applied by exploring the real power generation from power stations. The ED problem is formulated by Eq. (3.11) and transmission losses are formulated by Eq. (3.12)

Swarm Representation

Real power generations are the decision variable for ED problem. Swarm formation is done by real power generations. The position of the particle in the swarm is replica of the set of real power generation of all committed generators. Let if there are NG generators in the system, the representation of the particle position would be described in the form of vector length NG. Let NP particle are taken in the swarm, the representation of complete swarm in the matrix form as noted below:

$$\text{Swarm} = \begin{bmatrix} P_{11} & P_{12} & .. & .. & P_{1NG} \\ P_{21} & P_{22} & .. & .. & P_{2NG} \\ . & . & P_{ij} & .. & . \\ P_{NP1} & P_{NP2} & .. & .. & P_{NPNG} \end{bmatrix}$$

Swarm Initialization

The initialization of each element of above described swarm matrix is occurred randomly within capacity constraints depend upon Eq. (3.11c). The initialization of the particle velocities done through this inequality:

$$V_j^{min} \le V_{ij} \le V_j^{max} \quad (\text{i}=1,2\ldots\text{NP; j}=1,2\ldots\text{NG}) \qquad (4.4)$$

There is assurance of producing new particles satisfying capacity constraints from the velocity-initialization scheme. For jth dimension, the limit of maximum velocity is formulated as

$$V_j^{max} = \frac{P_j^{max} - P_j^{min}}{\alpha} \tag{4.5}$$

Where α is the selected number interval in the jth dimension.

Evaluation of Objective function

To satisfy energy constraints, one of the committed generators is chosen as a dependent/slack generator d and this is obtained by

$$P_d{}^j = Z^j \quad (i=1,2\ldots NG; \; j=1,2\ldots L) \tag{4.6}$$

Where

$$Z = P_D - \sum_{i=1, i\neq d}^{NG} P_i \tag{4.7}$$

If there is the violation of the operating limits by the production of the dependent/slack generator then it is set by equation below

$$P_i{}^j = \begin{cases} P_i{}^{min} \;; & P_i{}^j < P_i{}^{min} \\ P_i{}^{min} \;; & P_i{}^j > P_i{}^{max} \\ P_i{}^j \;; & P_i{}^{min} \leq P_i{}^j \leq P_i{}^{max} \end{cases} \quad (i=1,2\ldots NG;\; i\neq d;\; j=1,2\ldots L) \tag{4.8}$$

When the limitation of the value of dependent generator is done then penalty factor term is applied in the objective function in order to penalize the fitness value. This function is formulated as

$$f^j = \mathrm{F}\,(P_i{}^j) - \varphi^j \quad (j = 1,2\ldots L) \tag{4.9}$$

where

Penalty factor is as $$\varphi^j = \begin{cases} (P_d{}^j - P_d{}^{min})^2 \;; & P_d{}^j < P_d{}^{min} \\ (P_d{}^{max} - P_d{}^j)^2 \;; & P_d{}^j > P_d{}^{max} \\ 0 \;; & P_d{}^{min} \leq P_d{}^j \leq P_d{}^{max} \end{cases} \tag{4.10}$$

Best Position Initialization

In PSO strategy, pbest and Gbest are essential parts. pbest is obtained by the position with minimum value of objective function. Gbest is the best value among Pbest.

Particle Movement

The particles in the swarm are accelerated to new position. This is done through counting new velocities to their existing positions. The new updated velocities and positions are as following below

$$v_{ij}^{new} = \omega.\ v_{ij} + c_1 * \text{rand}()*(pbest - P_{ij}) + c_2 * \text{Rand}()*(gbest_d - P_{ij}) \quad (4.11)$$

$$P_{ij}^{new} = P_{ij} + v_{ij}^{new} \quad (i=1,2...NP;\ \ j=1,2...NG) \quad (4.12)$$

Updating the Best and the Worst Positions

Objective function values evaluate the particles in the new positions. In this state, the up gradation of Pbest of particles is done. The Gbest is taken out among Pbest. An objective value at Gbest is retaining as f_{best} .

Stopping Criterion

A stochastic optimization approach can be terminated by many criterions at hand. Some of them are maximum no. of iterations, no. of functions evaluations and tolerance. In this present case, maximum no. of iteration is taken for this task. Here if stopping criterion is not fulfill then this mentioned procedure would be run through again with incremental t value.

4.4 ED with Transmission Loss through PSO

Implementation

The main task of ED is to allocate the load demand among participating generators at minimum possible cost without violating any system constraints. The PSO can be applied by exploring the real power generation from power stations. The ED problem is formulated by Eq. (3.11) and transmission losses are formulated by Eq. (3.12)

Swarm Representation

Real power generations are the decision variable for ED problem. Swarm formation is done by real power generations. The position of the particle in the swarm is replica of the set of real power generation of all committed generators. Let if there are NG generators in the system, the representation of the particle position would be described in the form of vector length NG. Let NP particle are taken in the swarm, the representation of complete swarm in the matrix form as noted below:

$$\text{Swarm} = \begin{bmatrix} P_{11} & P_{12} & .. & .. & P_{1NG} \\ P_{21} & P_{22} & .. & .. & P_{2NG} \\ . & . & P_{ij} & .. & . \\ P_{NP1} & P_{NP2} & .. & .. & P_{NPNG} \end{bmatrix}$$

Swarm Initialization

The initialization of each element of above described swarm matrix is occurred randomly within capacity constraints depend upon Eq. (3.11c). The initialization of the particle velocities done through this inequality:

$$V_j^{min} \leq V_{ij} \leq V_j^{max} \quad \text{(i=1,2...NP; j=1,2...NG)} \qquad (4.13)$$

There is assurance of producing new particles satisfying capacity constraints from the velocity-initialization scheme. For jth dimension, the limit of maximum velocity is formulated as

$$V_j^{max} = \frac{P_j^{max} - P_j^{min}}{\alpha} \qquad (4.14)$$

Where α is the selected number interval in the jth dimension.

Evaluation of Objective function

To satisfy energy constraints, one of the committed generators is chosen as a dependent/slack generator d and this is obtained by

$$P_d{}^j = W^j \quad (i=1,2\ldots NG;\ \ j=1,2\ldots L) \tag{4.15}$$

Where

$$W^j = \left(-Y^j \pm \sqrt{(Y^j)^2 - 4XZ^j} \right) \Big/ (2X) \quad \text{when } (Y^j)^2 - 4XZ^j \geq 0$$

With X = B_{dd}

$$Y = \sum_{k=1,k\neq d}^{NG} (B_{kd} + B_{dk})\, P_k{}^j + B_{do} - 1$$

$$Z^j = P_D + B_{00} + \sum_{k=1,k\neq d}^{NG} \sum_{l=1,l\neq d}^{NG} P_k{}^j\, B_{kl} P_l{}^j + \sum_{k=1,k\neq d}^{NG} B_{ko}\, P_k{}^j - \sum_{k=1,k\neq d}^{NG} P_k{}^j$$

If there is the violation of the operating limits by the production of the dependent/slack generator then it is set by equation below

$$P_i{}^j = \begin{cases} P_i{}^{min} \ ; & P_i{}^j < P_i{}^{min} \\ P_i{}^{min} \ ; & P_i{}^j > P_i{}^{max} \\ P_i{}^j \ ; & P_i{}^{min} \leq P_i{}^j \leq P_i{}^{max} \end{cases} \quad (i=1,2\ldots NG;\ i\neq d;\ j=1,2\ldots L) \tag{4.17}$$

When the limitation of the value of dependent generator is done then penalty factor term is applied in the objective function in order to penalize the fitness value. This function is formulated as

$$f^j = \mathrm{F}\,(P_i{}^j) - \varphi^j \quad (j = 1,2\ldots L) \tag{4.18}$$

where

Penalty factor is as $$\varphi^j = \begin{cases} (P_d{}^j - P_d{}^{min})^2 \ ; & P_d{}^j < P_d{}^{min} \\ (P_d{}^{max} - P_d{}^j)^2 \ ; & P_d{}^j > P_d{}^{max} \\ 0 \ ; & P_d{}^{min} \leq P_d{}^j \leq P_d{}^{max} \end{cases} \tag{4.19}$$

Best Position Initialization

In PSO strategy, pbest and Gbest are essential parts. Pbest is obtained by the position with minimum value of objective function. Gbest is the best value among Pbest.

Particle Movement

The particles in the swarm are accelerated to new position. This is done through counting new velocities to their existing positions. The new updated velocities and positions are as following below

$v_{ij}{}^{new}$ = ω. v_{ij}+ c_1* rand ()*($pbest$ -P_{ij}) + c_2*Rand ()*($gbest_d$ -P_{ij}) (4.20)

$P_{ij}{}^{new}$ = P_{ij} + $v_{ij}{}^{new}$ (i=1,2…NP; j=1,2…NG) (4.21)

Updating the Best and the Worst Positions

Objective function values evaluate the particles in the new positions. In this state, the up gradation of Pbest of particles is done. The Gbest is taken out among Pbest. An objective value at Gbest is retaining as f_{best} .

Stopping Criterion

A stochastic optimization approach can be terminated by many criterions at hand. Some of them are maximum no. of iterations, no. of functions evaluations and tolerance. In this present case, maximum no. of iteration is taken for this task. Here if stopping criterion is not fulfill then this mentioned procedure would be run through again with incremental t value.

SUMMARY

This chapter firstly summarizes the PSO and then elaborates the ELD procedures neglecting transmission loss and considering transmission loss through PSO approach. It also outlines the flow chat of basic PSO.

CHAPTER-5

RESULTS AND DISCUSSION

Case Study-1: Three Unit System

Case Study-2: Six Unit System

CHAPTER-5

5.1 CASE STUDY-1: Three Unit System

The fuel cost is in Rs. /h of three thermal plants of a power system are

C_1 = 200 + 7.0P_1+ 0.008P_1^2 Rs. /h

C_2 = 180 + 6.3P_2 + 0.009P_2^2 Rs. /h

C_3 = 140 + 6.8P_3 + 0.007P_3^2 Rs. /h

WhereP_1, P_2 and P_3 are in MW. Plants outputs are subject to the following limits

10MW $\le P_1 \le$ 85 MW

10MW $\le P_2 \le$ 80 MW

10MW $\le P_3 \le$ 70 MW

Total system load is 150 MW

The B matrices of the loss formula for this system are given below. They are given in per unit on a 100 MVA base are follows

$$B = \begin{matrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{matrix}$$

B_0 = [0.0003 0.0031 0.0015]

B_{00} = [0.00030523]

5.1.1 ED NEGLECTING TRANSMISSION LOSSES

5.1.1.1 Result through Lambda-iteration method neglecting transmission losses:

P_1 = 35.0907 MW

P_2 = 64.0317 MW

P_3 = 50.7776 MW Total generation cost = 1582.65 Rs/h

5.1.1.2 Result through PSO method neglecting transmission loss:

The following PSO parameters are considered

- Population size = 100
- Inertia weight factor ω, ω_{max} = 0.9 and ω_{min} = 0.4
- Acceleration constant c_1 = 2 & c_2 = 2
- $V_{pd}{}^{max}$ = 0.5 $P_d{}^{max}$, $V_{pd}{}^{min}$ = - 0.5 $P_d{}^{min}$

The result as follows

P_1 = 36.4325 MW

P_2 = 63.1597 MW

P_3 = 50.4057 MW Total generation cost = 1580.02 Rs/h

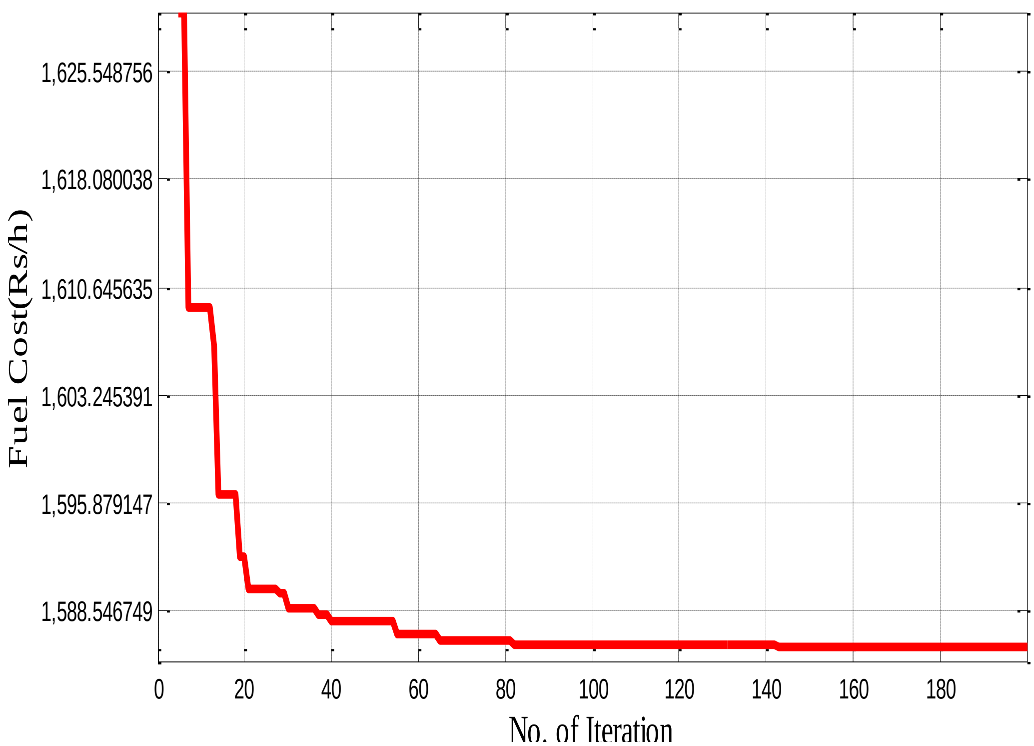


Fig 5.1: Fuel cost curve considering without transmission losses

In this figure, fuel cost is converged at cost of 1580.02 Rs/h. Here transmission losses are neglected. There are 200 numbers of iteration is taken.

5.1.2 ED WITH TRANSMISSION LOSSES

5.1.2.1 Result through Lambda-iteration method with transmission losses:

P_1 = 33.4701 MW

P_2 = 64.0974 MW

P_3 = 55.1011 MW

Power Loss = 2.66 MW

Total generation cost = 1599.90 Rs/h

5.1.2.2 Result through PSO method with transmission loss:

The following PSO parameters are considered

- Population size = 100
- Inertia weight factor ω, ω_{max} = 0.9 and ω_{min} = 0.4
- Acceleration constant c_1 = 2 & c_2 = 2
- ${V_{pd}}^{max}$ = 0.5 ${P_d}^{max}$, ${V_{pd}}^{min}$ = - 0.5 ${P_d}^{min}$

The result as follows

P_1 = 33.0858 MW

P_2 = 64.4545 MW

P_3 = 54.8325 MW

Power Loss = 2.37 MW

Total generation cost = 1598.79 Rs/h

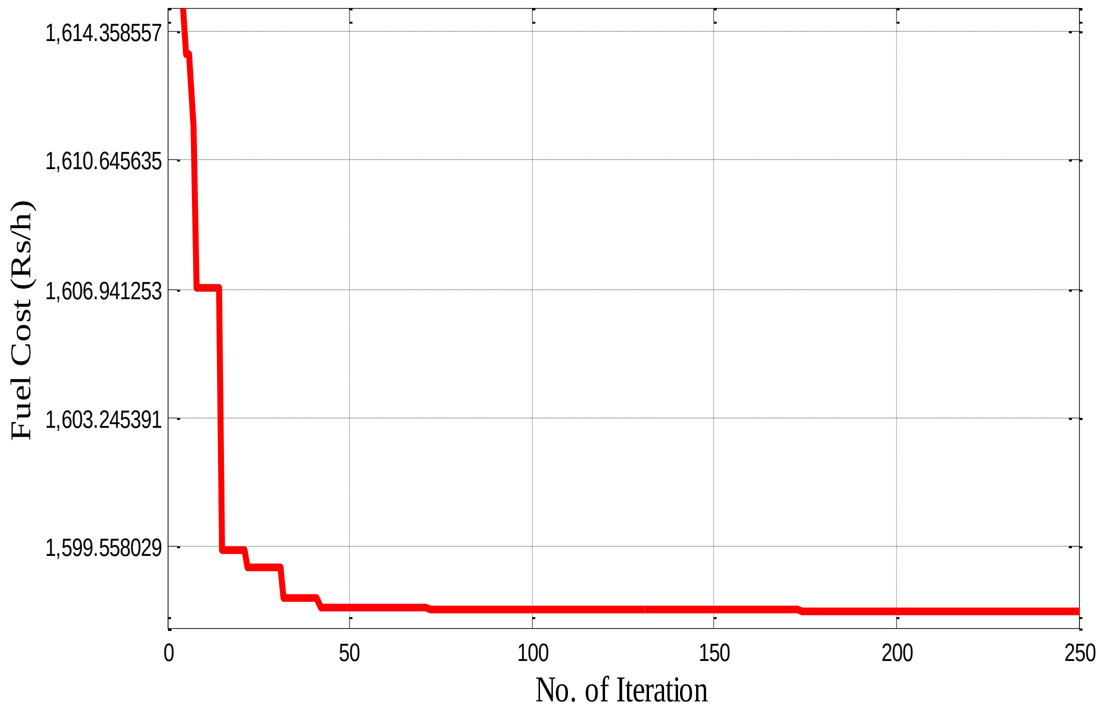


Fig 5.2: Fuel cost curve with transmission losses

In this figure, fuel cost is converged at cost of 1598.79 Rs/h. Here transmission losses are 2.37MW. There are 250 numbers of iteration is taken.

5.1.3 Fuel Cost Comparison

Table 5.1: Fuel Cost Comparison

Name	Lambda-iteration method	PSO method
Without loss	1582.65 Rs/h	1580.03 Rs/h
With loss	1599.90 Rs/h	1598.79 Rs/h

5.2 CASE STUDY- 2: Six Unit System

The fuel cost in Rs./h of three plants of a power system are

$$C_1 = 756.79886+38.53P_1+0.15240{P_1}^2 \text{ Rs/h}$$

$$C_2 = 451.32513+46.15P_2+0.10587{P_2}^2 \text{ Rs/h}$$

C_3 = 1049.9977+40.39P_3+0.02803$P_3{}^2$ Rs/h

C_4 = 1243. 5311+38.30P_4+0.03546$P_4{}^2$ Rs/h

C_5 = 1658.5596+36.32P_5+0.02111 $P_5{}^2$Rs/h

C_6 = 1356.6592+38.27 P_6+0.01799$P_6{}^2$Rs/h

The operating ranges are

10 MW $\leq P_1 \leq$ 125 MW

10 MW $\leq P_2 \leq$ 150 MW

35 MW $\leq P_3 \leq$ 225 MW

35 MW $\leq P_4 \leq$ 210 MW

130 MW $\leq P_5 \leq$ 325 MW

125 MW $\leq P_6 \leq$ 315 MW

Table 5.2

B-Coefficient (in the order of 10^{-4})

$$B_{mn} = \begin{bmatrix} 1.40 & 0.17 & 0.15 & 0.19 & 0.26 & 0.22 \\ 0.17 & 0.60 & 0.13 & 0.16 & 0.15 & 0.20 \\ 0.15 & 0.13 & 0.65 & 0.17 & 0.24 & 0.19 \\ 0.19 & 0.16 & 0.17 & 0.71 & 0.30 & 0.25 \\ 0.26 & 0.15 & 0.24 & 0.30 & 0.69 & 0.32 \\ 0.22 & 0.20 & 0.19 & 0.25 & 0.32 & 0.85 \end{bmatrix}$$

5.2.1 ED Neglecting Transmission Line Loss

5.2.1.1 Result through Lambda-iteration method

Table5.3: Result through Lambda-iteration method

S. No.	Load Demand(MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Fuel Cost(Rs/h)
1	600	21.2001	10	81.9207	95.3205	205.5486	185.9898	31445.92
2	700	24.9786	10	101.8765	110.3283	233.7816	218.7627	36003.24

3	800	28.7882	10.1030	123.90	125.834	260.0180	251.3266	40676.10
4	900	32.5215	10.5192	143.4569	143.1827	287.0532	282.8771	45465.09
5	1000	35.9598	15.982	163.4301	158.1345	313	313.4936	50363.70

5.2.1.2 Result through PSO method

The following PSO parameters are considered

- Population size = 100
- Inertia weight factor ω, ω_{max} = 0.9 and ω_{min} = 0.4
- Acceleration constant c_1 = 2 & c_2 = 2
- ${V_{pd}}^{max}$ = 0.5 ${P_d}^{max}$, ${V_{pd}}^{min}$ = - 0.5 ${P_d}^{min}$

Table5.4: Result through PSO method

S. No.	Load Demand(MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Fuel Cost(Rs/h)
1	600	21.1801	10	82.0887	94.372	205.3665	186.9924	31145.65
2	700	24.9626	10	102.664	110.6361	232.6865	219.0505	36003.17
3	800	28.7452	10	123.2393	126.9002	260	251.1085	40676.02
4	900	32.4969	10.8159	143.6467	143.0316	287.1036	282.9050	45464.15
5	1000	36.0840	15.982	163.159	158.4555	313.0122	313.3070	50362.48

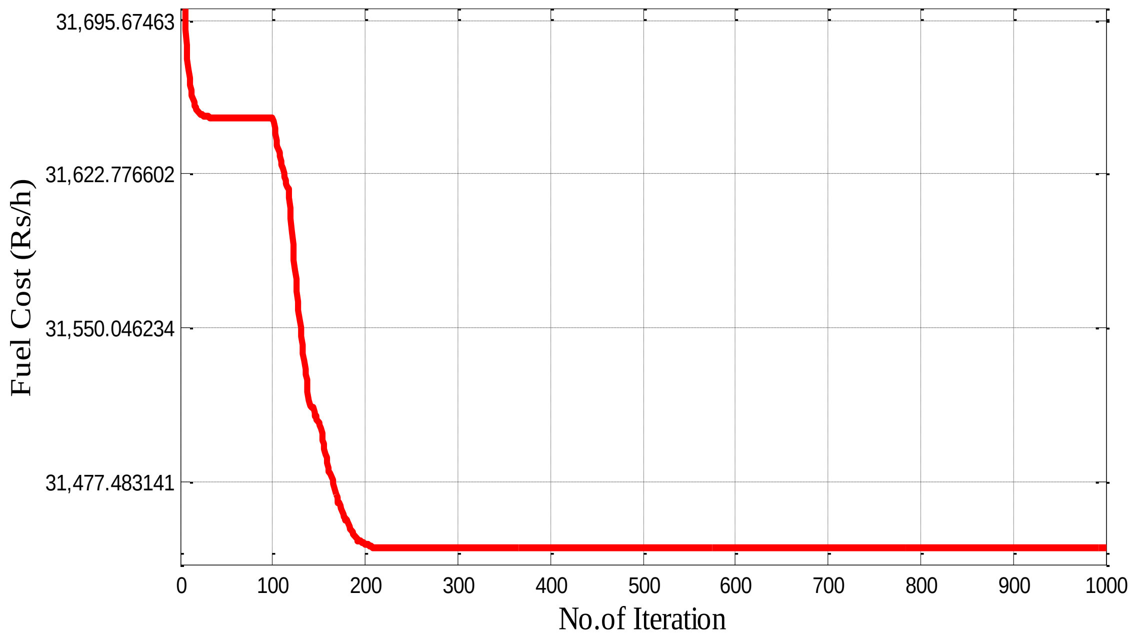


Fig 5.3: Fuel cost curve without transmission loss for 600 MW load demand

In this figure, fuel cost is converged at 31145.65 Rs/h for 600 MW power demand. Here transmission losses are neglected. There are 1000 numbers of iteration is taken.

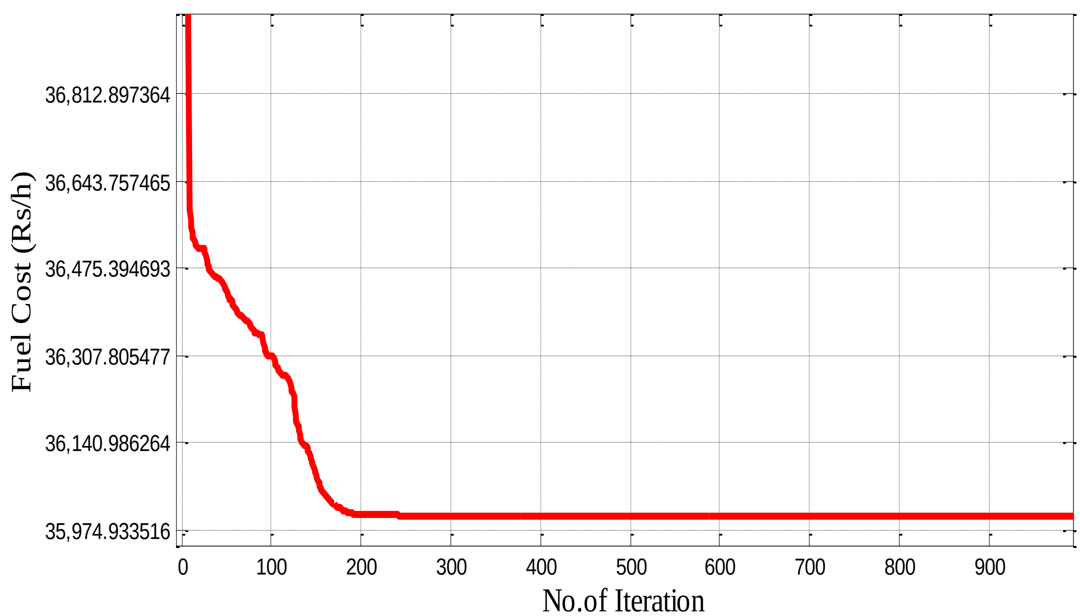


Fig 5.4: Fuel cost curve without transmission loss for 700 MW load demand

In this figure, fuel cost is converged at 36003.17 Rs/h for 700 MW power demand. Here transmission losses are neglected. There are 1000 numbers of iteration is taken.

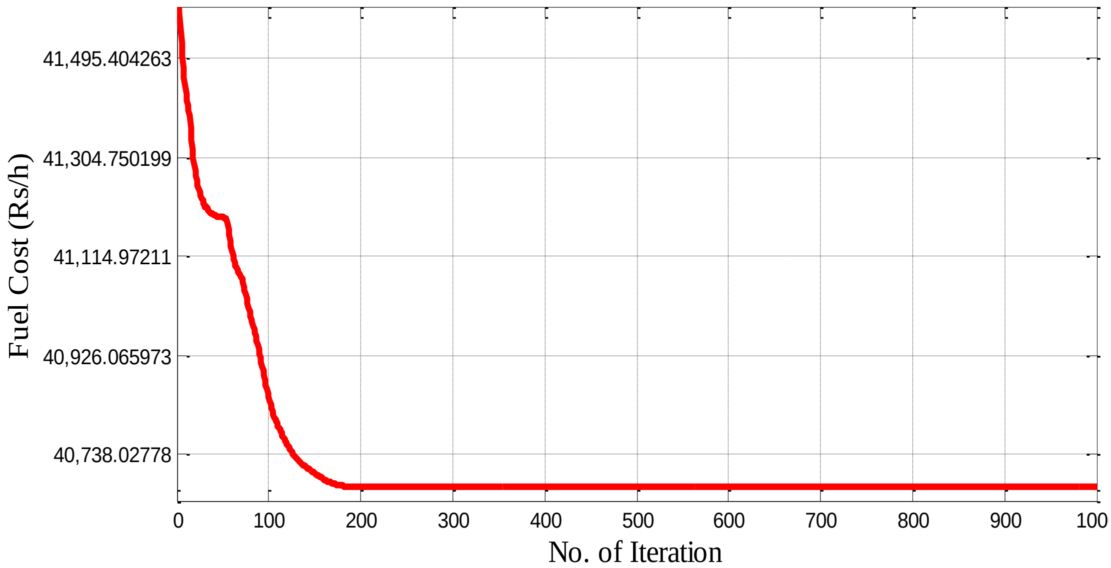


Fig 5.5: Fuel cost curve without transmission loss for 800 MW load demand

In this figure, fuel cost is converged at 40676.02 Rs/h for 800 MW power demand. Here transmission losses are neglected. There are 1000 numbers of iteration is taken.

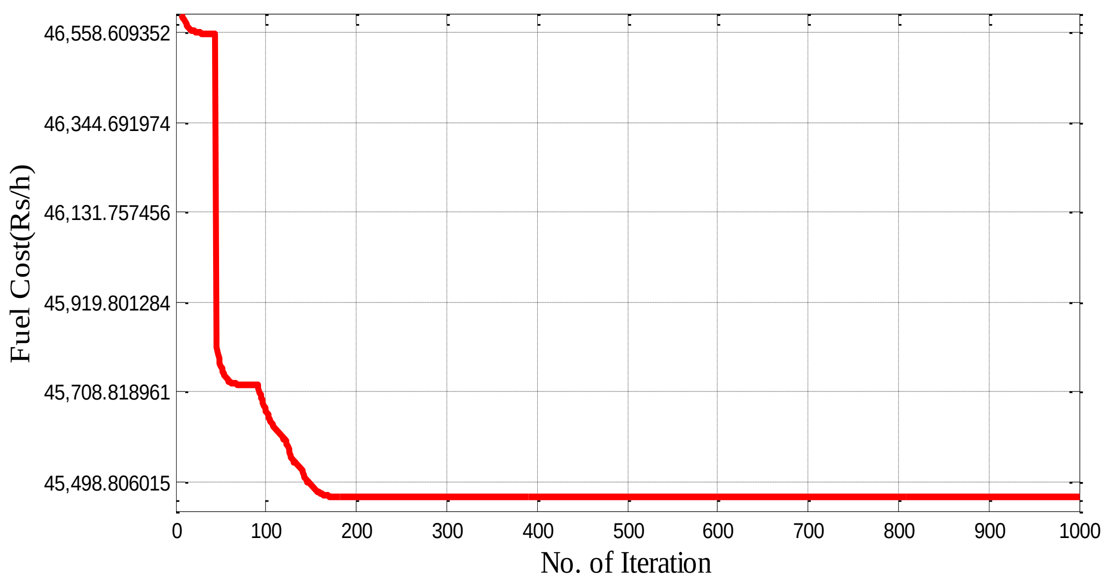


Fig 5.6: Fuel cost curve without transmission loss for 900 MW load demand

In this figure, fuel cost is converged at 45464.15 Rs/h for 900 MW power demand. Here transmission losses are neglected. There are 1000 numbers of iteration is taken.

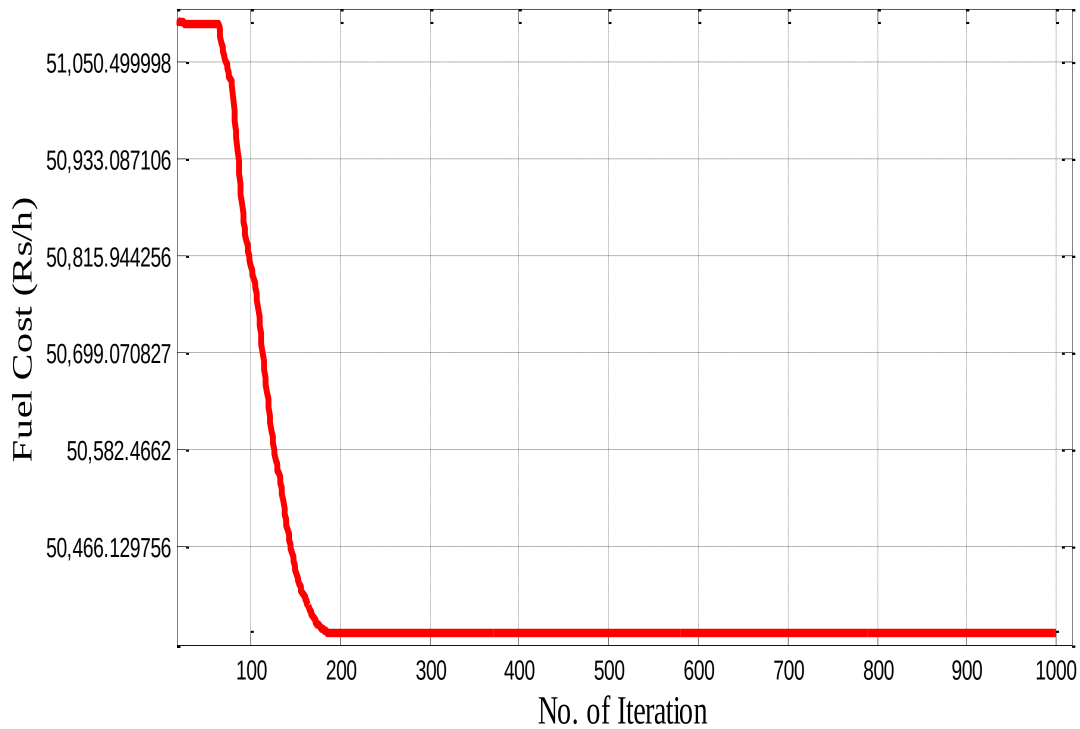


Fig 5.7: Fuel cost curve without transmission loss for 1000 MW load demand

In this figure, fuel cost is converged at 50363.48 Rs/h for 1000 MW power demand. Here transmission losses are neglected. There are 1000 numbers of iteration is taken.

5.2.1.3 Cost Comparison

Table 5.5: Cost comparison of lambda-iteration method and PSO method without transmission loss

S. No.	Load demand (MW)	Lambda –iteration method (Rs/h)	PSO method(Rs/h)
1	600	31445.92	31145.65
2	700	36003.24	36003.17
3	800	40676.10	40676.02
4	900	45465.09	45464.15
5	1000	50363.70	50363.48

5.2.2 ED WITH TRANSMISSION LINE LOSSES

5.2.2.1 Result through Lambda-iteration method

Table 5.6: Result through Lambda-iteration method

S. No.	Load Demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Power loss (MW)	Fuel Cost(Rs/h)
1	600	23.7909	10.22	95.25	101.2309	202.9670	181.34	14.7988	32132.29
2	700	28.290	10.0901	118.9873	118	230.2372	213.9068	19.5114	36912.32
3	800	32.9521	14.7126	141.5988	136.0345	258.1009	243.8011	27.5	41897.25
4	900	36.9889	22.1821	163.01	153.2168	284.1482	273.0581	32.6131	47045.32
5	1000	40.3969	28.1002	187	171.2136	310.7210	303.1006	40.5323	52362.07

5.2.2.2 Result through PSO method

The following PSO parameters are considered

- Population size = 100
- Inertia weight factor ω, ω_{max} = 0.9 and ω_{min} = 0.4
- Acceleration constant c_1 = 2 & c_2 = 2
- ${V_{pd}}^{max}$ = 0.5 ${P_d}^{max}$, ${V_{pd}}^{min}$ = - 0.5 ${P_d}^{min}$

Table 5.7: Result through PSO method

S. No.	Load Demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Power loss (MW)	Fuel Cost(Rs/h)
1	600	23.8602	10	95.6394	100.7081	202.8315	181.1978	14.2373	32094.72
2	700	28.290	10	118.9583	118.6747	230.7630	212.7449	19.43	36912.22
3	800	32.586	14.4839	141.5475	136.0435	257.6624	243.0073	25.33	41896.70
4	900	36.8480	21.0774	163.9304	153.2263	284.1696	272.7301	31.98	47045.25
5	1000	41.1657	27.7786	186.5604	170.5795	310.8297	302.568	39.4821	52361.65

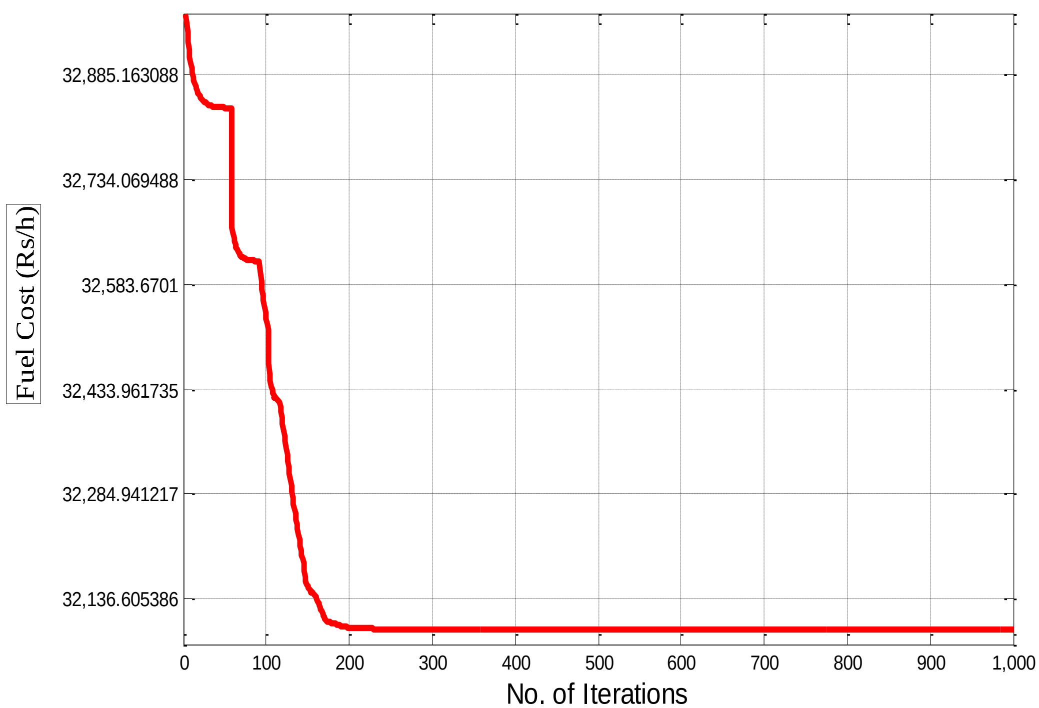


Fig 5.8: Fuel cost curve for load demand 600MW with transmission loss

In this figure, fuel cost is converged at 32094.72 Rs/h for 600 MW power demand. Here transmission losses are 14.23 MW. There are 1000 numbers of iteration is taken.

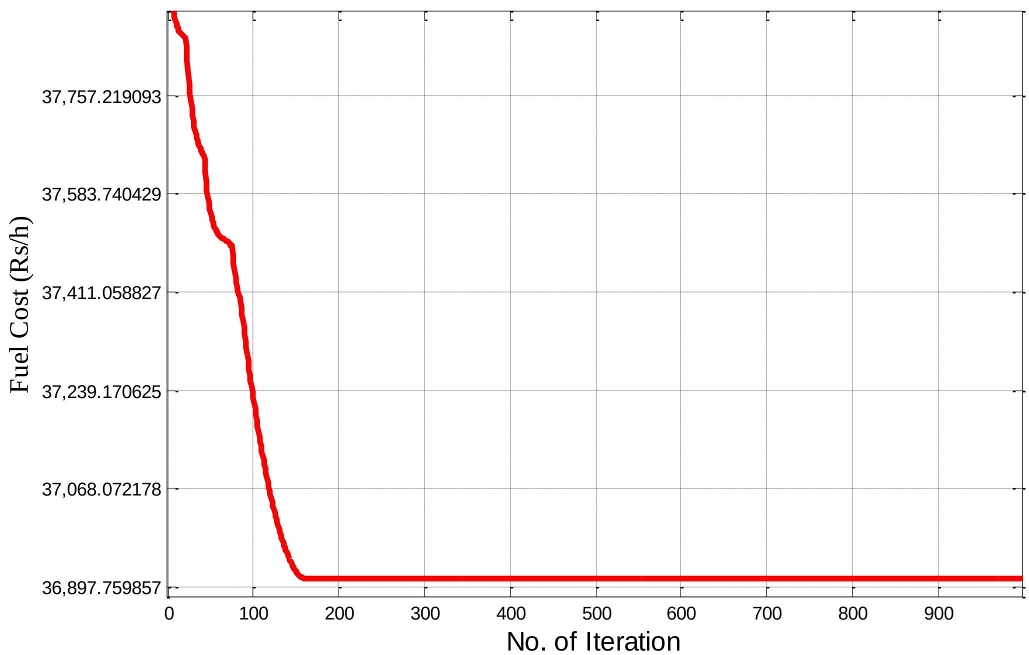


Fig 5.9: Fuel cost curve for load demand 700MW with transmission loss

In this figure, fuel cost is converged at 36912.22 Rs/h for 700 MW power demand. Here transmission losses are 19.43 MW. There are 1000 numbers of iteration is taken.

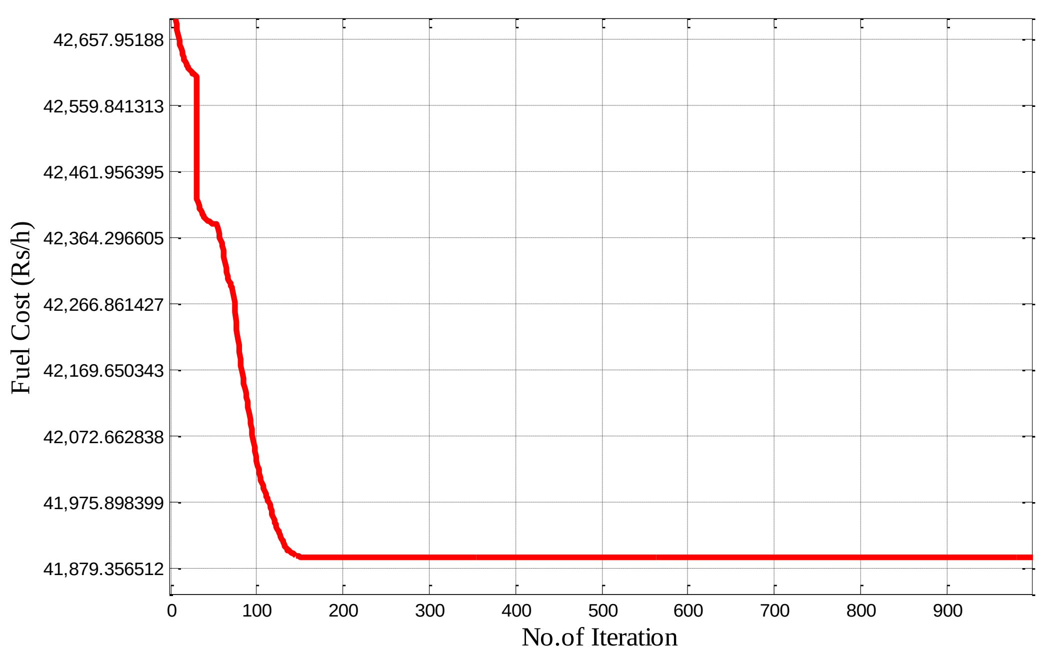


Fig 5.10: Fuel cost curve for load demand 800MW with transmission loss

In the above figure, fuel cost is converged at 41896.70 Rs/h for 800 MW power demand. Here transmission losses are 25.33 MW. There are 1000 numbers of iteration is taken.

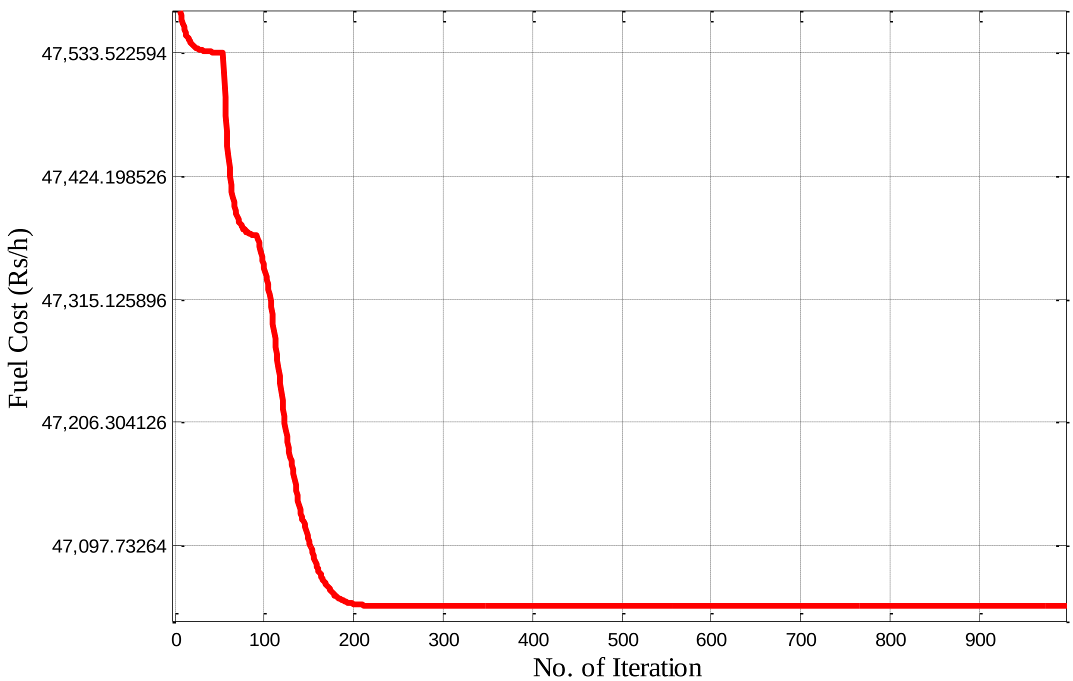


Fig 5.11: Fuel cost curve for load demand 900MW with transmission loss

In this figure, fuel cost is converged at 47045.25 Rs/h for 900 MW power demand. Here transmission losses are 31.98 MW. There are 1000 numbers of iteration is taken.

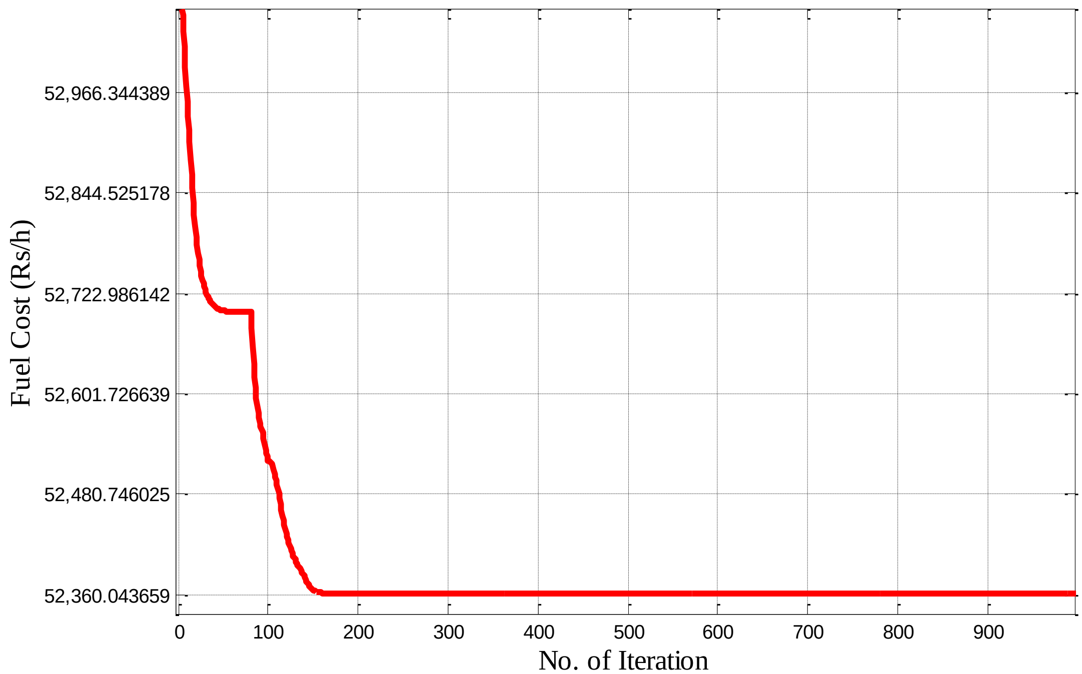


Fig 5.12: Fuel cost curve for load demand 1000MW with transmission loss

In this figure, fuel cost is converged at 52361.65 Rs/h for 1000 MW power demand. Here transmission losses are 39.48 MW. There are 1000 numbers of iteration is taken.

5.2.2.3 Cost comparison

Table 5.8: Cost comparison of lambda-iteration method and PSO method with transmission loss

S. No.	Load demand (MW)	Lambda –iteration method (Rs/h)	PSO method(Rs/h)
1	600	32132.29	32094.72
2	700	36912.32	36912.22
3	800	41897.25	41896.70
4	900	47045.32	47045.25
5	1000	52362.07	52361.65

CHAPTER-6

CONCLUSION AND FUTURE SCOPE

Conclusion

Future Scope

CHAPTER-6

6.1 Conclusion

In this study, two methods (lambda iteration method and PSO) are implemented to examine the superiority between them. Lambda iteration method is conventional method but PSO is population based search algorithm. PSO displayed high quality solution along with convergence characteristics. The plotted graphs for both three unit system and six unit systems showed the property of convergence characteristic of PSO. The reliability of PSO is also superior. The faster convergence in PSO approach is due to the employment of inertia weight factor which is set to be at 0.9 to 0.4(In fact, it decreases linearly in one run). As far as the fuel cost is concerned, it is small for three unit system but it is reasonably good for six unit system.

6.2 Future Scope

Many progresses are introducing the PSO. Some of them are PSO based ANN with simulated annealing technique, adaptive PSO, quantum inspired PSO etc. are in queue. These new coming approaches are coming with better results, high quality of solution and convergence characteristics.

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