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Comparison between Newton –Rephson Method and Particle Swarm Optimization in the Analysis of Economic Load Dispatch

مقارنة بين طريقة نيوتن رافسون و عناصر السرب المثلى لتحليل التوزيع الاقتصادي للحمولة

A Thesis Submitted in Partial Fulfillment for the Requirements for the Degree of M.Sc. in Electrical Engineering (Power)

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الآيـة

قال تعالى :

"وَفَوْقَ كُلِّ ذِي عِلْمٍ عَلِيمٌ"

يوسف 76

Dedication

To the human teacher,,
Prophet Muhammad peace be upon him.

To the man who carried me on his right shoulder and on the other shoulder carried all the worries of the world
Who was a help to me in seeking knowledge, my father.

To the crown of my head
To the light of my way
To whom she was praying at night for my success, my mother.

to my husband for his support and patient

To those who were my strength after God
To those who taught me the science of life, my sisters.

To those who donates their time and knowledge, my teachers.

Acknowledgement

Even if we collected all the letters of the language we won't thank you enough,,
Thanks and gratitude to our teacher and the supervisor of this project

Thanks for your knowledge, thanks for your time, thanks for you.

Abstract

The objective of the thesis is to introduce the importance of Economic load Dispatch in a power system. The Economic Dispatch means, to find the generation of the different units in the power system so that the total fuel cost is minimum and at the same time the total demand and transmission line losses at any instant must be met by the total generation considering the generation limits constrain. These constraints formulates the economic dispatch for finding the optimal power flow of all the online generating units that minimizes the total fuel cost, while satisfying an equality constraint and a set of inequality constraints. The thesis discuss how the Economic Dispatch problem being solved by using the methods of Newton Raphson (NR) and Particle Swarm Optimization (PSO). The two methods had been implemented to IEEE 39 New England test system by using MATLAB software R2010a .The results of the two methods after simulation in MATLAB were analyzed and conclude that the Particle Swarm Optimization method is more efficient than the Newton Raphson method.

المستخلص

الهدف من هذا البحث التعريف بأهمية التوليد الاقتصادي لمنظومة القدره. تعريف التوليد الاقتصادي هو ايجاد التوليد الامثل لجميع الوحدات في منظومة القدره لجعل مجموع تكلفة الوقود هي الأقل ،مجموع الطلب و المفاقيد اللحظيه يساوي مجموع التوليد مع مراعاة حدود التوليد. حدود التوليد تساعد في ايجاد تدفق القدره الامثل من جميع الوحدات لتقليل تكلفة الوقود الكليه مع مراعاة حدود المساواة و عدم المساواة. هذه الاطروحه تناقش حل مشكلة التوليد الاقتصادي باستخدام طريقة نيوتن رافسون وطريقة استمثال عناصر السرب. تم تطبيق الطريقتين لمنظومة 39 قضيب توصيل لانكلترا الجديدة الاختباريه. في برنامج الماتلاب و تم المقارنه بين نتائج الطريقتين وجد ان طريقة استمثال عناصر السرب اكثر كفاءه من طريقة نيوتن رافسون، وتم تصميم البرنامج ليطبق لأي عدد من وحدات التوليد لكلا الطريقتين.

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LIST OF SYMBOLS

V	Volt
I	Current
R	Resistance
P	Active Power
Q	Reactive Power
C_i	Fuel cost Function
a, b & d	Generator fuel cost characteristic
P_G	Real power generation
Q_G	Reactive power generation
P_D	Real power Demand
P_L	power Losses
B_{ij}	B-coefficient to calculate the power loss formula
L	Lagragian multiplier
λ	Lambda
p_d	Particle position
v_d	Particle velocity
d	No of Particle
$pbest_d$	The best previous position of particle d
gbest	the best particle among all particles represented
iter	No of iteration
ITmax	Maximum No of iteration
ω	is the inertia weight factor
C_1 and C_2	cognitive and social parameters, respectively
$rand_1$ and $rand_2$	random values in [0, 1]
w_{max} and w_{min}	maximum and minimum weight factor
k	No of iteration

LIST OF ABBREVIATIONS

IEEE	The Institute of Electrical And Electronics Engineers
NR	Newton Raphson Method
PSO	Particle Swarm Optimization
IFC	Incremental Fuel Cost
BTU	British Thermal Unit
ITL	Incremental Transmission Losses

1.1 Background

Economic operation and planning of electric energy generating systems have always been given proper attention in the electric power system industry. A saving in the cost of generation represents a significant reduction in the operating cost (including the fuel cost) and hence this area has warranted a great deal of attention from operating and planning engineers. The original problem of economic dispatch of thermal power generating systems used to be solved by numerous methods. However, with the development of mathematical tools and advance computational methods, the economic scheduling of generators has become more accurate and can be applied even in complex networks. Thermal scheduling being of prime importance, hydrothermal coordination scheduling has emerged as another aspect of economic scheduling. The basic purpose of economic operation of power system is to reduce fuel cost for the operation of power system economic operation is achieved when the generators in the system share load to minimize overall generation cost. The main economic factor in the power system operation is the cost of generating real power [1].

As power systems are getting larger and more complicated due to the increase of load demand, the fossil fuel demand of thermal power plants increases which causes rising costs and rising emissions into the environment. Therefore, optimization has become essential for the operation of power system utilities in terms of fuel cost savings and environmental preservation [2].

The optimal operating point of a power generation system is where the operating level of each generating unit is adjusted such that the total cost of delivered power is at a minimum. In an energy management system, Economic Dispatch is used to determine each generating level in the system in order to minimize the total generator fuel cost or total generator cost and emission of thermal units while still covering load demand plus transmission losses [3].

Recently, methods based on artificial intelligence have been widely used for solving optimization problems. These methods have the advantage that they can deal with complex problems that cannot be solved by conventional methods. Moreover, these methods are easy to apply due to their simple mathematical structure and easy to combine with other methods to hybrid systems adding the strengths of each single method [4].

1.2 Problem Statement

Economic dispatch determines the optimal real power outputs for the generating units online so that fuel cost of generating units is minimized while all unit and system operating constraints are satisfied. By using conventional method and artificial intelligent methods in this thesis and compare between the two results to find the optimal generation schedule the methods were applied to IEEE 39 New England bus system with 10 generator units.

1.3 Objective

The main objective is to minimize the overall cost of production of power generation considering all system constrains by using conventional method *(Newton Raphson Method);* and intelligent method (*Particle Swarm Optimization*) in MatLab program, and to compare between the two methods.

1.4 Thesis Layout

The thesis organization is summarized as follow:

- Chapter one about research background, thesis problem and objectives.
- Chapter two about the economic operation in power system

- Chapter three discusses the conventional and artificial intelligent methods in power systems.
- Chapter four summarized the results of the software simulation in MatLab by using Newton Raphson (NR) and Particle Swarm Optimization (PSO) techniques.
- Chapter five gives thesis conclusion and recommendations.

2.1 Introduction

Generating plants have different characteristics which give different generating costs at any load. Therefore proper scheduling of plants for minimum cost of optimal operation becomes important. and because the cost characteristics of each generating unit are non-linear the problem of achieving the minimum cost becomes non-linear problem [5].

Economic dispatch is generation allocation problem and defined as the process of calculating the generation of the generating units so that the system load is supplied entirely and most economically subject to the satisfaction of the constraints and it is very important and essential daily optimization procedure in the system operation.

The optimal system operation, in general, involves the consideration of economy of operation, system security, emissions at certain fossil-fuel plants, and optimal releases of water at hydro-generation, etc. All these considerations may make conflicting requirements and usually a compromise has to be made for optimal system operation.

Since the basic purpose of economic operation of power system is to reduce the fuel cost for the operation of power system, economic operation achieved when the generation in the system share load to minimize overall generation cost. The main economic factor in the power system operation is the cost of generation real power. In any power system this cost has two components,

(i) The fixed cost being determined by the capital investment, interest charged on the money borrowed, tax paid, labor charge, salary given to staff and any other expenses that continue irrespective to the load on the power system.

(ii) The variable cost, a function of loading on generating units, losses daily load requirement and purchase or sale of power [1].

2.2 Generator Incremental Cost Curve

The analysis of the problems associated with the controlled operation of power systems contains many parameters of interest. Fundamental to the economic operating problem is the set of input-output characteristics of a thermal power generation unit as in Figure 2.1 [4].

From the input output curves, the incremental fuel cost (IFC) curve can be obtained. The IFC is defined as the ratio of a small change in the input to the corresponding small change in the output [1].

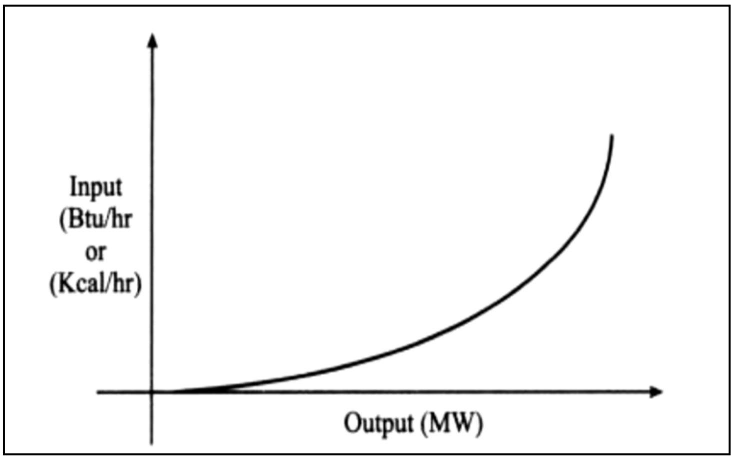


Figure 2.1: Input – Output Characteristic of Steam Turbine

$$IFC = \frac{\Delta Input}{\Delta Output} = \frac{\Delta F}{\Delta P_G} \quad (2.1)$$

Where Δ represents small changes.

As the Δ quantities become progressively smaller, it is seen that IFC is $\frac{d(Input)}{d(Output)}$ and is expressed in cost currency/MWhr. A typical plot of the IFC versus output power is shown in Figure 2.2.

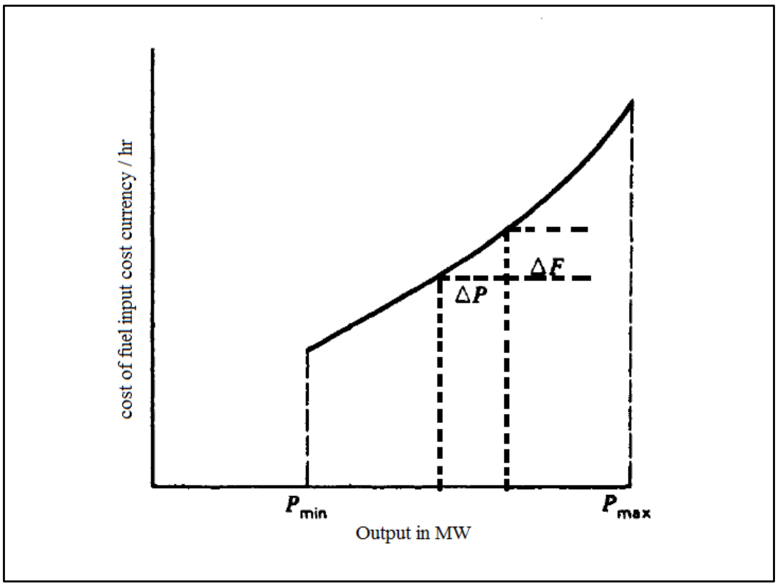


Figure 2.2: Incremental Fuel Cost Curve

Mathematically, the IFC curve can be obtained from the cost curve.

The cost curve,

$$C_i = \frac{1}{2} a_i P_{G_i}^2 + b_i P_{G_i} + d_i \text{ (Second degree polynomial)} \tag{2.2}$$

The IFC,

$$\frac{dC_i}{dP_{G_i}} = (IFC) = a_i P_{G_i} + b_i \text{ (linear approximation) for all } i = 1,2,3,\ldots n \tag{2.3}$$

Where $\frac{dC_i}{dP_{G_i}}$ is the ratio of incremental fuel energy input in BTU to the incremental energy output in KWh, which is called ‘the incremental heat rate’ .

2.3 *Optimal Generation Scheduling Considering Of Transmission Losses:*

In a practical system, a large amount of power is being transmitted through the transmission network, which causes power losses in the network (P_L) as shown in Figure 2.3.

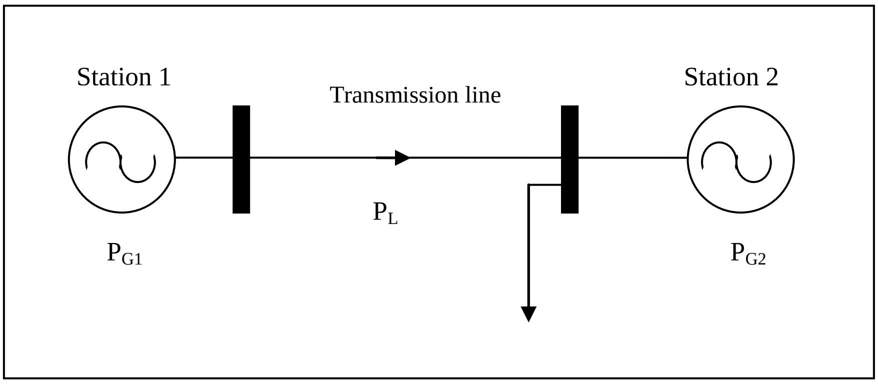


Figure 2.3: Transmission Network

2.3.1 Mathematical Modeling :

Consider the objective function:

$$C = \sum_{i=1}^{n} C_i(P_{G_i}) \tag{2.4}$$

Minimize equation (2.4) subjected to equality and inequality constrains:

(i) Equality constraint

The real-power balance equation, i.e., total real power generation P_{G_i} minus the total losses P_L should be equal to the real-power demand P_D :

$$\sum_{i=1}^{n} P_{G_i} - P_L = P_D \quad \text{or} \quad \sum_{i=1}^{n} P_{G_i} - P_L - P_D = 0 \tag{2.5}$$

(ii) Inequality constrain

Always there will be upper and lower limits for the real and reactive-power generation at each station. The inequality constrain represented:

(a) In term of real –power generation as

$$P_{G_i(\min)} \le P_{G_i} \le P_{G_i(\max)} . \tag{2.6}$$

(b) in term of reactive-power generation as

$$Q_{G_i(\min)} \le Q_{G_i} \le Q_{G_i(\max)} \tag{2.7}$$

(c) in term of voltage at each of the station should be maintain with certain limits

$$V_{i(\min)} \le V_i \le V_{i(\max)} \qquad (2.8)$$

The optimal solution should be obtained by minimizing the cost function satisfying constrain equations (2.5) to (2.8) [1].

2.4 Transmission Loss in Term of Real Power Generation:

Transmission loss P_L is expressed without loss of accuracy as a function of real-power generation. The power loss is expressed in *B-coefficients* or *loss coefficients*. The final equation is as below

$$ITL = \frac{\partial P_L}{\partial P_{G_i}} = \sum_{j=1}^{n} 2B_{ij}P_{G_i} \qquad (2.9)$$

2.5 Plant Scheduling Methods:

At the plant level, several operating procedure were adopted in the past leading efficient operation resulting in economy

(i) *Base loading to capacity*

The turbo generators are successively loaded to their rated capacities in the order of their efficiencies. That is to say, that the most efficient unit will get greater share in load allocation which is a natural solution to the problem.

(ii) Base loading to most efficient load

In this case the heat rate characteristics are considered and the turbo-generator units are successively loaded to their most efficient loads in increasing order of their heat rates. In both the above methods thermodynamic considerations assumed importance and the schedules will not differ from each other much.

(iii) Proportional loading to capacity

A third method that was considered as a thumb rule in the absence of any technical data is to load the generating units in proportion to their rated capacities as stated on the name plates [6].

2.6 *Optimal Power Flow:*

In an Optimal Power flow, the values of some or all of the control variables need to be found so as to optimize (minimize or maximize) a predefined objective. It is also important that the proper problem definition with clearly stated objectives be given at the onset. The quality of the solution depends on the accuracy of the model studied. Objectives must be modeled and its practicality with possible solutions.

Objective function takes various forms such as fuel cost, transmission losses and reactive source allocation. Usually the objective function of interest is the minimization of total production cost of scheduled generating units. This is most used as it reflects current economic dispatch practice and importantly cost related aspect is always ranked high among operational requirements in Power Systems.

2.7 *Optimal Power Flow Solution Methodologies*

The OPF methods are broadly grouped as Conventional and Intelligent. The conventional methodologies include the well known techniques like Gradient method, Newton method, Quadratic Programming method, Linear Programming method and Interior point method. Intelligent methodologies include the recently developed and popular methods like Genetic Algorithm, Particle swarm optimization.

The solution methodologies can be broadly grouped in to two namely:

1. Conventional (classical) methods
2. Intelligent methods.

The further sub classification of each methodology is given below as per the Tree diagram.

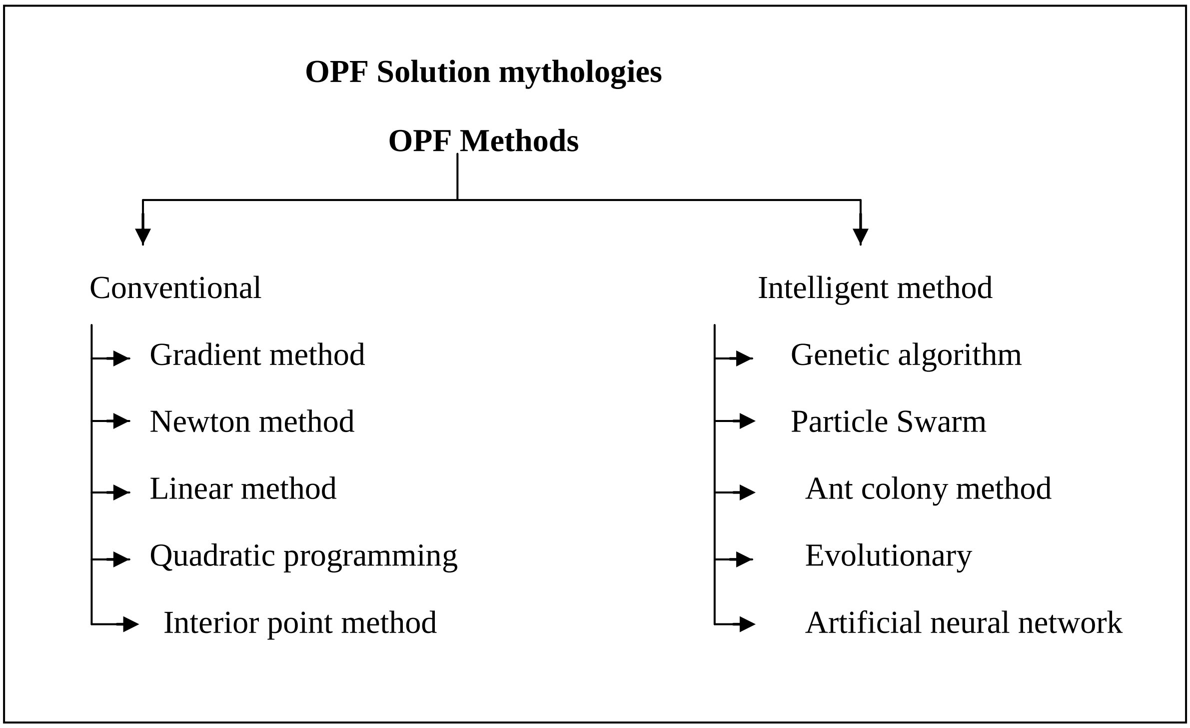


Figure 2.4 Tree Diagram Indicating Optimal Power Flow Methodologies

2.7.1 Conventional Methodologies

The list of OPF Methodologies is presented in the Tree diagram Figure 2.4. It starts with Gradient Method.

2.7.1.1 Gradient Method:

The Generalized Reduced Gradient is applied to the OPF problem with the main motivation being the existence of the concept of the state and control variables, with load flow equations providing a nodal basis for the elimination of state variables. With the availability of good load flow packages, the sensitivity information needed is provided. This in turn helps in obtaining a reduced problem in the space of the control variables with the load flow equations and the associated state variables eliminated.

2.7.1.2 Newton Method:

In the area of Power systems, Newton's method is well known for solution of Power Flow. It has been the standard solution algorithm for the power flow problem for a long time the Newton approach is a flexible formulation that can be adopted to develop different OPF algorithms suited to the requirements of different applications. Although the Newton approach exists as a concept entirely apart from any specific method of implementation, it would not be possible to develop practical OPF programs without employing special sparsity techniques. The concept and the techniques together comprise the given approach. Other Newton-based approaches are possible.

Newton's method is a very powerful solution algorithm because of its rapid convergence near the solution. This property is especially useful for power system applications because an initial guess near the solution is easily attained. System voltages will be near rated system values, generator outputs can be estimated from historical data, and transformer tap ratios will be near 1.0 p.u.

2.7.1.3 Linear Programming Method

Linear Programming (L.P) method treats problems having constraints and objective functions formulated in linear form with non negative variables. Basically the simple method is well known to be very effective for solving LP problems.

The Linear Programming approach has been advocated on the grounds that

(a) The L.P solution process is completely reliable.

(b) The L.P solutions can be very fast.

(c) The accuracy and scope of linearised model is adequate for most engineering purposes.

It may be noted that point (a) is certainly true while point (b) depends on the specific algorithms and problem formulations. The observation (c) is frequently valid since the transmission network is quasi linear, but it needs to be checked out for any given system and application.

2.7.1.4 Quadratic Programming Method

Quadratic Programming (QP) is a special form of NLP. The objective function of QP optimization model is quadratic and the constraints are in linear form. Quadratic Programming has higher accuracy than LP – based approaches. Especially the most often used objective function is a quadratic.

The NLP having the objective function and constraints described in Quadratic form is having lot of practical importance and is referred to as quadratic optimization. The special case of NLP where the objective function is quadratic (i.e. is involving the square, cross product of one or more variables) and constraints described in linear form is known as quadratic programming. Derivation of the sensitivity method is aimed at solving the NLP on the computer. Apart from being a common form for many important problems, Quadratic Programming is also very important because many of the problems are often solved as a series of QP or Sequential Quadratic Programming (SQP) problems.

Quadratic Programming based optimization is involved in power systems for maintaining a desired voltage profile, maximizing power flow and minimizing generation cost. These quantities are generally controlled by complex power generation which is usually having two limits. Here minimization is considered as maximization can be determined by changing the sign of the objective function. Further, the quadratic functions are characterized by the matrices and vectors.

2.7.1.5 Interior Point Method

It has been found that, the projective scaling algorithm for linear programming proposed by N. Karmarkar is characterized by significant speed advantages for large problems reported to be as much as 12:1 when compared to the simplex method Further, this method has a polynomial bound on worst-case running time that is better than the ellipsoid algorithms. Karmarkar's algorithm is significantly different from Dantzig's simplex method. Karmarkar's interior point rarely visits too many extreme points before an optimal point is found. In addition, the IP method stays in the interior of the polytope and tries to position a current solution as the "center of the universe" in finding a better direction for the next move. By properly choosing the step lengths, an optimal solution is achieved after a number of iterations. Although this IP approach requires more computational time in finding a moving direction than the traditional simplex method, better moving direction is achieved resulting in less iteration. In this way, the IP approach has become a major rival of the simplex method and has attracted attention in the optimization community. Several variants of interior points have been proposed and successfully applied to optimal power flow.

The Interior Point Method is one of the most efficient algorithms. The IP method classification is a relatively new optimization approach that was applied to solve power system optimization problems; it solves a large scale linear programming problem by moving through the interior, rather than the boundary as in the simple method, of the feasible reason to find an optimal solution. The IP method was originally proposed to solve linear programming problems; however later it was implemented to efficiently handle quadratic programming problems.

2.7.2 Intelligent Methodologies:

Intelligent methods include Genetic Algorithm and Particle Swarm Optimization methods.

2.7.2.1 Binary Coded Genetic Algorithm Method:

The drawbacks of conventional methods were presented in Section 2.7.1. All of them can be summarized as three major problems:

- Firstly, they may not be able to provide optimal solution and usually getting stuck at a local optimal.
- Secondly, all these methods are based on assumption of continuity and differentiability of objective function which is not actually allowed in a practical system.
- Finally, all these methods cannot be applied with discrete variables, which are transformer taps. It is observed that Genetic Algorithm (GA) is an appropriate method to solve this problem, which eliminates the above drawbacks. GAs differs from other optimization and search procedures in four ways [8]:

- GAs work with a coding of the parameter set, not the parameters themselves. Therefore GAs can easily handle the integer or discrete variables.
- GAs search within a population of points, not a single point. Therefore GAs can provide a globally optimal solution.
- GAs use only objective function information, not derivatives or other auxiliary knowledge. Therefore GAs can deal with non-smooth, non-continuous and non-differentiable functions which are actually exist in a practical optimization problem.
- GAs use probabilistic transition rules, not deterministic rules[4].

The Main GA features over other search techniques are:

1. GA algorithm is a multipath that searches many peaks in parallel and hence reducing the possibility of local minimum trapping.
2. GA works with a coding of parameters instead of the parameters themselves. The coding of parameter will help the genetic operator to evolve the current state into the next state with minimum computations.
3. GA evaluates the fitness of each string to guide its search instead of the optimization function.

2.7.2.2 Particle Swarm Optimization Method

Particle swarm optimization (PSO) is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling.

In PSO, the search for an optimal solution is conducted using a population of particles, each of which represents a candidate solution to the optimization problem. Particles change their position by flying round a multidimensional space by following current optimal particles until a relatively unchanged position has been achieved or until computational limitations are exceeded. Each particle adjusts its trajectory towards its own previous best position and towards the global best position attained till then. PSO is easy to implement and provides fast convergence for many optimization problems and has gained lot of attention in power system applications recently.

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 .In PSO, each particle makes it s decision using its own experience together with its neighbor’s experience.

In this thesis, PSO was used as an intelligent method in MATLAB, for comparison with the conventional method (Newton Raphson).

3.1Introduction

The optimal power flow (OPF) was first introduced by Carpentier in 1962. The goal of OPF is to find the optimal settings of a given power system network that optimize the system objective functions such as total generation cost, system loss, bus voltage deviation, emission of generating units, number of control actions, and load shedding while satisfying its power flow equations, system security, and equipment operating limits. Different control variables, some of which are generators real power outputs and voltages, transformer tap changing settings, phase shifters, switched capacitors, and reactors, are manipulated to achieve an optimal network setting based on the problem formulation.

According to the selected objective functions, and constraints, there are different mathematical formulations for the OPF problem. They can be broadly classified as follows:

1. Linear problem in which objectives and constraints are given in linear forms with continuous control variables
2. Nonlinear problem where either objectives or constraints or both combined are nonlinear with continuous control variables
3. Mixed - integer linear problems when control variables are both discrete and continuous

Various techniques were developed to solve the OPF problem. The algorithms may be classified into three groups:

1. Conventional optimization methods,
2. Intelligence search methods, and
3. Non-quantity approach to address uncertainties in objectives and constraints [8].

3.2 Conventional Optimization Method:

Traditionally, conventional methods are used to effectively solve OPF. The application of these methods had been an area of active research in the recent past. The ***conventional methods*** are based on mathematical programming approaches and used to solve different size of OPF problems. To meet the requirements of different objective functions, types of application and nature of constraints, the popular conventional methods is further sub divided into the following:

(a) Gradient Method

(b) Newton-Raphson Method

(c) Linear Programming Method

(d) Quadratic Programming Method

(e) Interior Point Method

Even though, excellent advancements have been made in classical methods, they suffer with the following disadvantages: In most cases, mathematical formulations have to be simplified to get the solutions because of the extremely limited capability to solve real-world large-scale power system problems. They are weak in handling qualitative constraints. They have poor convergence, may get stuck at local optimum, they can find only a single optimized solution in a single simulation run, they become too slow if number of variables are large and they are computationally expensive for solution of a large system.

For this thesis *Newton-Raphson* method was implemented as a *conventional method* on the IEEE 39 New England test system to find the optimal power flow.

3.2.1 Newton – Raphson Method:

In the area of Power systems, Newton's method is well known for solution of Power Flow. It has been the standard solution algorithm for the power flow problem for a long time The Newton approach is a flexible formulation that can be adopted to develop different OPF algorithms suited to the requirements of different applications. Although the Newton approach exists as a concept entirely apart from any specific method of implementation, it would not be possible to develop practical OPF programs without employing special Sparsity techniques. The concept and the techniques together comprise the given approach. Other Newton-based approaches are possible.

Newton's method is a very powerful solution algorithm because of its rapid convergence near the solution. This property is especially useful for power system applications because an initial guess near the solution is easily attained. System voltages will be near rated system values, generator outputs can be estimated from historical data, and transformer tap ratios will be near 1.0 p.u.

3.2.1.1 Newton-Raphson Solution Algorithm:

Let us consider a *N*-bus power system having *NG* number of thermal power generators. Then the aim of optimal power flow problem is to minimize the cost of thermal power generation,

$$F_{c_{Total}} = \sum_{i=1}^{NG} F_{c_i} = \sum_{i=1}^{NG} \alpha_i (P_{g_i})^2 + \beta_i P_{g_i} + \gamma_i \text{ unit of cost/hr} \quad (3.1)$$

Subjected to

(i) Active power balance in the network

$$P_i(|V|, \delta) - P_{g_i} + P_{load} = 0 \text{ for i=1,2,3,....,N} \quad (3.2)$$

Where P_i = active power injection at i-th bus and is a function of |V| and δ. For load buses [i.e for i= (NG+1),(NG+2),…(N)], P_{g_i} =0;

(ii) Reactive power balance in the network

$$Q_i(V, \delta) - Q_{g_i} + Q_{load} = 0 \text{ for i=(NG+1),(NG+2),....,N} \quad (3.3)$$

Where Q_i = reactive power injection at i-th bus and also a function of |V| and δ. Q_{g_i} =reactive power generation at *i-th* bus;

(iii) Security related constrains *(also called soft constrain)*.these constrain are discussed in chapter two in equations (2.6) to (2.8).

The constraint minimization problem can be transformed into unconstrained one by augment the load flow constraints into objective function. The additional variables are known as the *Lagrange Multiplier Functions* or *Incremental Cost Function* in power system optimization. The *Lagrangian Function* then becomes

$$\mathrm{L}(\mathrm{P}_g.|V|,\delta)=\sum_{i=1}^{NG}F_c(P_{g_i})+\sum_{i=1}^{N}\lambda_{Pi}[P_i(|V|,\delta)-P_{g_i}-P_{load_i}]+\sum_{i=NG+1}^{N}\lambda_{qi}[Q_i(|V|,\delta)-Q_{g_i}-Q_{load_i}] \tag{3.4}$$

The optimization Problem is solved, only if the following equation satisfied,

$$\frac{\partial L}{\partial P_{g_i}}=\frac{\partial F}{\partial P_{g_i}}-\lambda_{p_i} \text{ for i=1,2,3,...,NG} \tag{3.5}$$

$$\frac{\partial L}{\partial \delta_i}=\sum_{k=1}^{N}\left[\lambda_{p_k}\frac{\partial P_k}{\partial \delta i}\right]+\sum_{k=NG+1}^{N}\left[\lambda_{q_k}\frac{\partial Q_k}{\partial \delta_i}\right] \text{ for i=2,3,...,NG} \tag{3.6}$$

From equation (3.4) we can write the following

$$\frac{\partial L}{\partial \lambda_{p_i}}=P_i\left(|V|,\delta\right)-P_{g_i}+P_{load_i} \text{for i=1,2,3,...,N} \tag{3.7}$$

And

$$\frac{\partial L}{\partial |V_i|}=\sum_{k=1}^{N}\left[\lambda_{p_k}\frac{\partial P_k}{\partial |V_i|}\right]+\sum_{k=NG+1}^{N}\left[\lambda_{q_k}\frac{\partial Q_k}{\partial |V_i|}\right] \text{ for i=NG+1,...,N} \tag{3.8}$$

Further to this

$$\frac{\partial L}{\partial \lambda_{q_i}}=Q_i\left(|V|,\delta\right)-Q_{g_i}+Q_{load_i} \text{for i=NG+1,...,N} \tag{3.9}$$

Any small variation in control variables about their initial values is obtained by forming differential as given below:

$$\sum_{k=1}^{NG}\frac{\partial^2 L}{\partial P_{g_i}\partial P_{g_k}}\Delta P_{g_k}+\sum_{k=2}^{N}\frac{\partial^2 L}{\partial P_{g_i}\partial \delta_k}\Delta\delta_k+\sum_{k=1}^{N}\frac{\partial^2 L}{\partial P_{g_i}\partial \lambda_{p_k}}\Delta\lambda_{p_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial P_{g_i}\partial \lambda_{q_k}}\Delta\lambda_{q_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial P_{g_i}\partial |V_k|}\Delta|V_k|=-\frac{\partial L}{\partial P_{g_i}}$$

For i=1,2,3,…,NG (3.10)

$$\sum_{k=1}^{NG}\frac{\partial^2 L}{\partial\delta_i\partial P_{g_k}}\Delta P_{g_k}+\sum_{k=2}^{N}\frac{\partial^2 L}{\partial\delta_i\partial\delta_k}\Delta\delta_k+\sum_{k=1}^{N}\frac{\partial^2 L}{\partial\delta_i\partial\lambda_{p_k}}\Delta\lambda_{p_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\delta_i\partial\lambda_{q_k}}\Delta\lambda_{q_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\delta_i\partial|V_k|}\Delta|V_k|=-\frac{\partial L}{\partial\delta_i}$$

For i=1,2,3,…,N (3.11)

$$\sum_{k=1}^{NG}\frac{\partial^2 L}{\partial\lambda_{p_i}\partial P_{g_k}}\Delta P_{g_k}+\sum_{k=2}^{N}\frac{\partial^2 L}{\partial\lambda_{p_i}\partial\delta_k}\Delta\delta_k+\sum_{k=1}^{N}\frac{\partial^2 L}{\partial\lambda_{p_i}\partial\lambda_{p_k}}\Delta\lambda_{p_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\lambda_{p_i}\partial\lambda_{q_k}}\Delta\lambda_{q_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\lambda_{p_i}\partial|V_k|}\Delta|V_k|=-\frac{\partial L}{\partial\lambda_{p_i}}$$

For i=1,2,3,…,N (3.12)

$$\sum_{k=1}^{NG}\frac{\partial^2 L}{\partial|V_i|\partial P_{g_k}}\Delta P_{g_k}+\sum_{k=2}^{N}\frac{\partial^2 L}{\partial|V_i|\partial\delta_k}\Delta\delta_k+\sum_{k=1}^{N}\frac{\partial^2 L}{\partial|V_i|\partial\lambda_{p_k}}\Delta\lambda_{p_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial|V_i|\partial\lambda_{q_k}}\Delta\lambda_{q_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial|V_i|\partial|V_k|}\Delta|V_k|=-\frac{\partial L}{\partial|V_i|}$$

For i=NG+1,…,N (3.13)

$$\sum_{k=1}^{NG}\frac{\partial^2 L}{\partial\lambda_{q_k}\partial P_{g_k}}\Delta P_{g_k}+\sum_{k=2}^{N}\frac{\partial^2 L}{\partial\lambda_{q_k}\partial\delta_k}\Delta\delta_k+\sum_{k=1}^{N}\frac{\partial^2 L}{\partial\lambda_{q_k}\partial\lambda_{p_k}}\Delta\lambda_{p_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\lambda_{q_k}\partial\lambda_{q_k}}\Delta\lambda_{q_k}+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\lambda_{q_k}\partial|V_k|}\Delta|V_k|=-\frac{\partial L}{\partial\lambda_{q_k}}$$

For i=NG+1,…,N (3.14)

Let us now differentiate equations (3.5) to (3.9) with respect to control variables (P_{gi}, δ_i, λ_{pi} , λ_{qi} and V_i) to get second order partial derivative required for equations (3.5) to (3.9) as follow:

$$\frac{\partial^2 L}{\partial P^2_{g_i}}=\frac{\partial^2 F_{c_i}}{\partial P^2_{g_i}}=2a_i$$ for *i*=1,2,3,…,NG (3.15)

$$\frac{\partial^2 L}{\partial P_{g_i}\partial P_{g_k}}=0$$ for *i*=1,2,3,…,NG;k=1,2,3,…,NG but i≠k (3.16)

$$\frac{\partial^2 L}{\partial P_{g_i}\partial\delta_k}=\frac{\partial^2 L}{\partial\delta_k\partial P_{g_i}}=0$$ for *i*=1,2,3,…,NG;k=1,2,3,…,N (3.17)

$$\frac{\partial^2 L}{\partial P_{g_i}\partial\lambda_{p_i}}=\frac{\partial^2 L}{\partial\lambda_{p_i}\partial P_{g_i}}=-1$$ for *i*=1,2,3,…,NG (3.18)

$$\frac{\partial^2 L}{\partial P_{g_i}\partial\lambda_{p_k}}=\frac{\partial^2 L}{\partial\lambda_{p_k}\partial P_{g_i}}=0$$ for *i*=1,2,3,…,NG;k=1,2,3,…,NG but i≠k (3.19)

$$\frac{\partial^2 L}{\partial P_{g_i}\partial\lambda_{q_k}}=\frac{\partial^2 L}{\partial\lambda_{q_k}\partial P_{g_i}}=0$$ for *i*=1,2,3,…,NG;k=1,2,3,…,N (3.20)

$$\frac{\partial^2 L}{\partial P_{g_i}\partial|V_k|}=\frac{\partial^2 L}{\partial|V_k|\partial P_{g_i}}=0$$ for *i*=1,2,3,…,NG;k=1,2,3,…,N (3.21)

Similarly, second order partial derivation required for equation (3.10) are obtained by differentiating equation (3.5) with respect to control variables , and are as follow:

$$\frac{\partial L}{\partial \delta_i}=\left[\lambda_{p_1}\frac{\partial P_1}{\partial \delta_i}+\lambda_{p_2}\frac{\partial P_2}{\partial \delta_i}+.....+\lambda_{p_N}\frac{\partial P_N}{\partial \delta_i}\right]+\left[\lambda_{q_{NG+1}}\frac{\partial Q_{NG+1}}{\partial \delta_i}+\lambda_{q_{NG+2}}\frac{\partial Q_{NG+2}}{\partial \delta_i}+.....+\lambda_{q_N}\frac{\partial Q_N}{\partial \delta_i}\right]$$

Differentiating both sides with respect to δ_k, we get

$$\frac{\partial^2 L}{\partial \delta_i \partial \delta_k}=\left[\lambda_{p_1}\frac{\partial^2 P_1}{\partial \delta_i \partial \delta_k}+\lambda_{p_2}\frac{\partial^2 P_2}{\partial \delta_i \partial \delta_{ki}}+.....+\lambda_{p_N}\frac{\partial^2 P_N}{\partial \delta_i \partial \delta_k}\right]+\left[\lambda_{q_{NG+1}}\frac{\partial^2 Q_{NG+1}}{\partial \delta_i \partial \delta_k}+\lambda_{q_{NG+2}}\frac{\partial^2 Q_{NG+2}}{\partial \delta_i \partial \delta_k}+.....+\lambda_{q_N}\frac{\partial^2 Q_N}{\partial \delta_i \partial \delta_k}\right]$$

$$\therefore \quad \frac{\partial^2 L}{\partial \delta_i \partial \delta_k}=\sum_{r=1}^{N}\lambda_{p_r}\frac{\partial^2 P_r}{\partial \delta_i \partial \delta_k}+\sum_{r=NG+1}^{N}\lambda_{q_r}\frac{\partial Q_r}{\partial \delta_i \partial \delta_k}$$ for i=2,3,..,N; k=2,3,..,N (3.22)

$$\frac{\partial^2 L}{\partial \delta_i \partial \lambda_{p_k}}=\frac{\partial P_k}{\partial \delta_i}$$ for i=2,3,..,N; k=2,3,..,N (3.23)

$$\frac{\partial^2 L}{\partial \delta_i \partial \lambda_{q_k}}=\frac{\partial Q_k}{\partial \delta_i}$$ for i=2,3,..,N; k=NG+1,..,N (3.24)

$$\frac{\partial^2 L}{\partial \delta_i \partial |V_k|}=\sum_{r=1}^{N}\lambda_{p_r}\frac{\partial^2 P_r}{\partial \delta_i \partial |V_k|}+\sum_{r=NG+1}^{N}\lambda_{q_r}\frac{\partial^2 Q_r}{\partial \delta_i \partial |V_k|}$$ for i=2,3,..,N; k=NG+1,..,N (3.25)

Next, second order partial derivatives required for equation (3.14) are obtained by differentiating equation (3.7) With respect to control variables:

$$\frac{\partial^2 L}{\partial \lambda_{p_i} \partial \delta_k}=\frac{\partial P_i}{\partial \delta_k}$$ for i=2,3,..,N; k=2,3,..,N (3.26)

$$\frac{\partial^2 L}{\partial \lambda_{p_i} \partial \lambda_{p_k}}=0$$ for i=1,2,3,..,N; k=1,2,3,..,N (3.27)

$$\frac{\partial^2 L}{\partial \lambda_{p_i} \partial \lambda_{q_k}}=0$$ for i=1,2,3,..,N; k=NG+1,..N (3.28)

$$\frac{\partial^2 L}{\partial \lambda_{p_i} \partial |V_k|}=\frac{\partial P_i}{\partial |V_k|}$$ for i=1,2,3,..,N; k=NG+1,..N (3.29)

Also, second order partial derivatives required for equation (3.13) are obtained be differentiating equation (3.8) with respect to control variables, and as follow:

$$\frac{\partial^2 L}{\partial |V_i| \partial \delta_k}=\sum_{r=1}^{N}\lambda_{p_r}\frac{\partial^2 P_r}{\partial |V_i| \partial \delta_k}+\sum_{r=NG+1}^{N}\lambda_{q_r}\frac{\partial^2 Q_r}{\partial |V_i| \partial \delta_k}$$ for i=NG+1,..,N; k=2,3,..,N (3.30)

$$\frac{\partial^2 L}{\partial |V_i| \partial \lambda_{p_k}} = \frac{\partial P_k}{\partial |V_i|} \quad \text{for } i\text{=NG+1,..,N; k=1,2,3,..,N} \quad (3.31)$$

$$\frac{\partial^2 L}{\partial |V_i| \partial \lambda_{q_k}} = \frac{\partial Q_k}{\partial |V_i|} \quad \text{for } i\text{=NG+1,..,N; k=NG+1,..,N} \quad (3.32)$$

$$\frac{\partial^2 L}{\partial |V_i| \partial |V_k|} = \sum_{r=1}^{N} \lambda_{p_r} \frac{\partial^2 P_r}{\partial |V_i| \partial |V_k|} + \sum_{r=NG+1}^{N} \lambda_{q_r} \frac{\partial^2 Q_r}{\partial |V_i| \partial |V_k|}$$

$$\text{for } i\text{=NG+1,..,N; k=NG+1,..,N} \quad (3.33)$$

Second order partial derivatives required for equation (3.14) are obtained by differentiating equation (3.9) with respect to control variables and are as follow:

$$\frac{\partial^2 L}{\partial \lambda_{q_i} \partial \delta_k} = \frac{\partial Q_i}{\partial \delta_k} \quad \text{for } i\text{=NG+1,..,N; k=2,3,..,N} \quad (3.34)$$

$$\frac{\partial^2 L}{\partial \lambda_{q_i} \partial \lambda_{p_k}} = 0 \quad \text{for } i\text{=NG+1,..,N; k=1,2,3,..,N} \quad (3.35)$$

$$\frac{\partial^2 L}{\partial \lambda_{q_i} \partial \lambda_{q_k}} = 0 \quad \text{for } i\text{=NG+1,..,N; k=NG+1,..,N} \quad (3.36)$$

$$\frac{\partial^2 L}{\partial \lambda_{q_k} \partial |V_k|} = \frac{\partial Q_k}{\partial |V_k|} \quad \text{for } i\text{=NG+1,..,N; k=NG+1,..,N} \quad (3.37)$$

Equations (3.10) to (3.14) can be rewritten as:

$$\frac{\partial^2 L}{\partial P_{g_i}^2} \Delta P_{g_i} + \frac{\partial^2 L}{\partial P_{g_i} \partial \lambda_{p_i}} \Delta \lambda_{p_i} = -\frac{\partial L}{\partial P_{g_i}} \quad \text{for } i\text{=1,2,3,…,NG} \quad (3.38)$$

$$\sum_{k=2}^{N} \frac{\partial^2 L}{\partial \delta_i \partial \delta_k} \Delta \delta_k + \sum_{k=1}^{N} \frac{\partial^2 L}{\partial \delta_i \partial \lambda_{p_k}} \Delta \lambda_{p_k} + \sum_{k=NG+1}^{N} \frac{\partial^2 L}{\partial \delta_i \partial \lambda_{q_k}} \Delta \lambda_{q_k} + \sum_{k=NG+1}^{N} \frac{\partial^2 L}{\partial \delta_i \partial |V_k|} \Delta |V_k| = -\frac{\partial L}{\partial \delta_i}$$

$$\text{for } i\text{=1,2,3,…,NG} \quad (3.39)$$

$$\frac{\partial^2 L}{\partial \lambda_{pi} \partial P_{gi}} \Delta P_{gi} + \sum_{k=2}^{N} \frac{\partial^2 L}{\partial \lambda_{pi} \partial \delta_k} \Delta \delta_k + \sum_{k=NG+1}^{N} \frac{\partial^2 L}{\partial \lambda_{pi} \partial |V_k|} \Delta |V_k| = -\frac{\partial L}{\partial \lambda_{pi}}$$

$$\text{for } i\text{=1,2,3,…,NG} \quad (3.40)$$

$$\sum_{k=2}^{N} \frac{\partial^2 L}{\partial |V_i| \partial \delta_k} \Delta \delta_k + \sum_{k=1}^{N} \frac{\partial^2 L}{\partial |V_i| \partial \lambda_{p_k}} \Delta \lambda_{p_k} + \sum_{k=NG+1}^{N} \frac{\partial^2 L}{\partial |V_i| \partial \lambda_{q_k}} \Delta \lambda_{q_k} + \sum_{k=NG+1}^{N} \frac{\partial^2 L}{\partial |V_i| \partial |V_k|} \Delta |V_k| = -\frac{\partial L}{\partial |V_i|}$$

$$\text{for } i\text{=NG+1,…,NG} \quad (3.41)$$

$$\sum_{k=2}^{N}\frac{\partial^2 L}{\partial\lambda_{q_i}\partial\delta_k}\Delta\delta_k+\sum_{k=NG+1}^{N}\frac{\partial^2 L}{\partial\lambda_{q_i}\partial|V_k|}\Delta|V_k|=-\frac{\partial L}{\partial\lambda_{q_i}} \qquad \text{for } i=NG+1,\ldots,NG$$

(3.42)

Equation (3.10) to(3.14) can be written as follow:

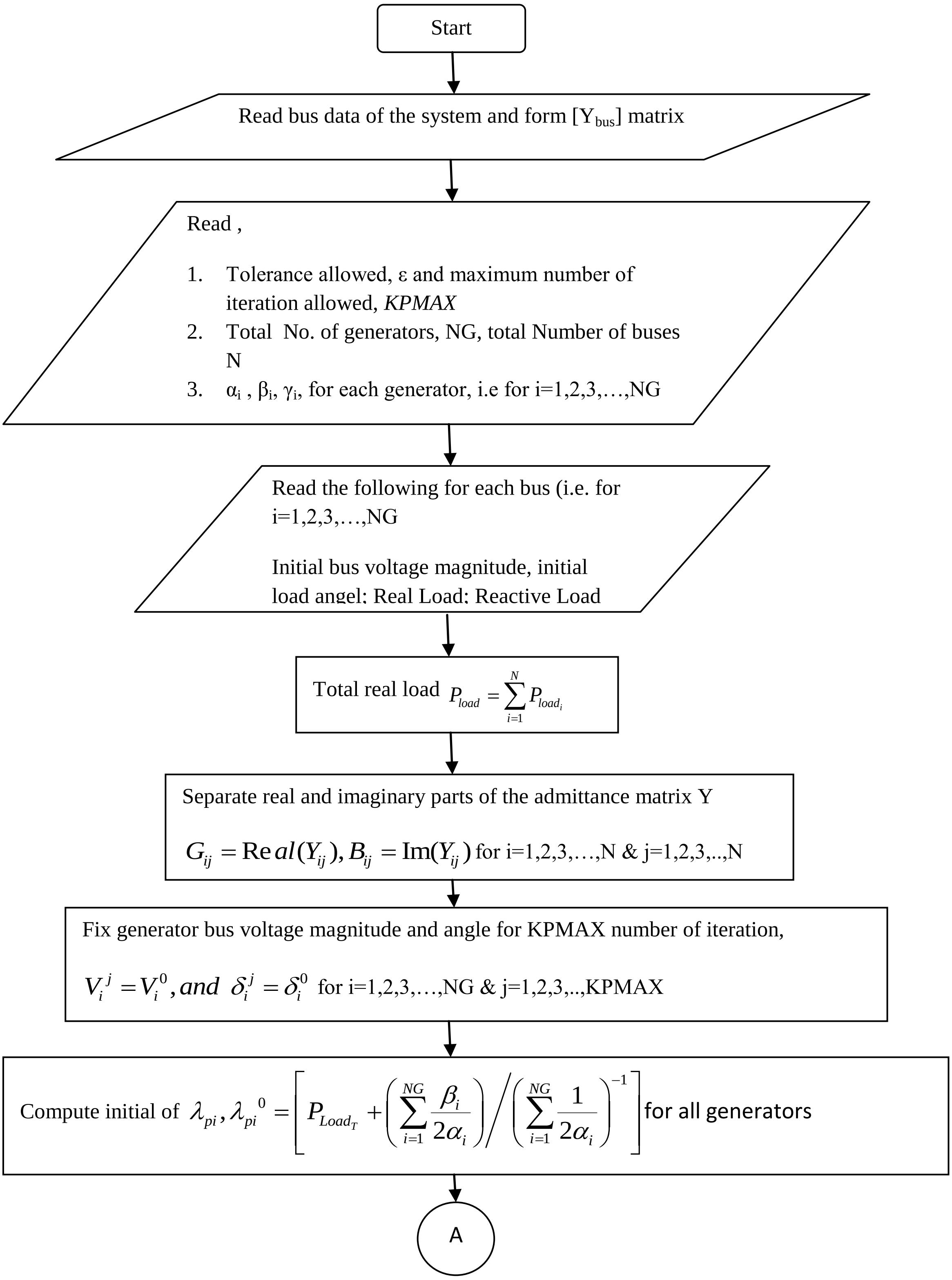
$$\begin{bmatrix} \frac{\partial^2 L}{\partial P_{g_i}\partial P_{g_k}} & 0 & \frac{\partial^2 L}{\partial P_{g_i}\partial\lambda_{p_k}} & 0 & 0 \\ 0 & \frac{\partial^2 L}{\partial\delta_i\partial\delta_k} & \frac{\partial^2 L}{\partial\delta_i\partial\lambda_{p_k}} & \frac{\partial^2 L}{\partial\delta_i\partial\lambda_{q_k}} & \frac{\partial^2 L}{\partial\delta_i\partial|V_k|} \\ \frac{\partial^2 L}{\partial\lambda_{p_i}\partial P_{g_k}} & \frac{\partial^2 L}{\partial\lambda_{p_i}\partial\delta_k} & 0 & 0 & \frac{\partial^2 L}{\partial\lambda_{p_i}\partial|V_k|} \\ 0 & \frac{\partial^2 L}{\partial|V_i|\partial\delta_k} & \frac{\partial^2 L}{\partial|V_i|\partial\lambda_{p_k}} & \frac{\partial^2 L}{\partial|V_i|\partial\lambda_{q_k}} & \frac{\partial^2 L}{\partial|V_i|\partial|V_k|} \\ 0 & \frac{\partial^2 L}{\partial\lambda_{q_i}\partial\delta_k} & 0 & 0 & \frac{\partial^2 L}{\partial\lambda_{q_i}\partial|V_k|} \end{bmatrix} \begin{bmatrix} \Delta P_{g_i} \\ \Delta\delta_i \\ \Delta\lambda_{p_i} \\ \Delta\lambda_{q_i} \\ \Delta|V_i| \end{bmatrix} = \begin{bmatrix} -\frac{\partial L}{\partial P_{g_i}} \\ -\frac{\partial L}{\partial\delta_i} \\ -\frac{\partial L}{\partial\lambda_{p_i}} \\ -\frac{\partial L}{\partial|V_i|} \\ -\frac{\partial L}{\partial\lambda_{q_i}} \end{bmatrix}$$

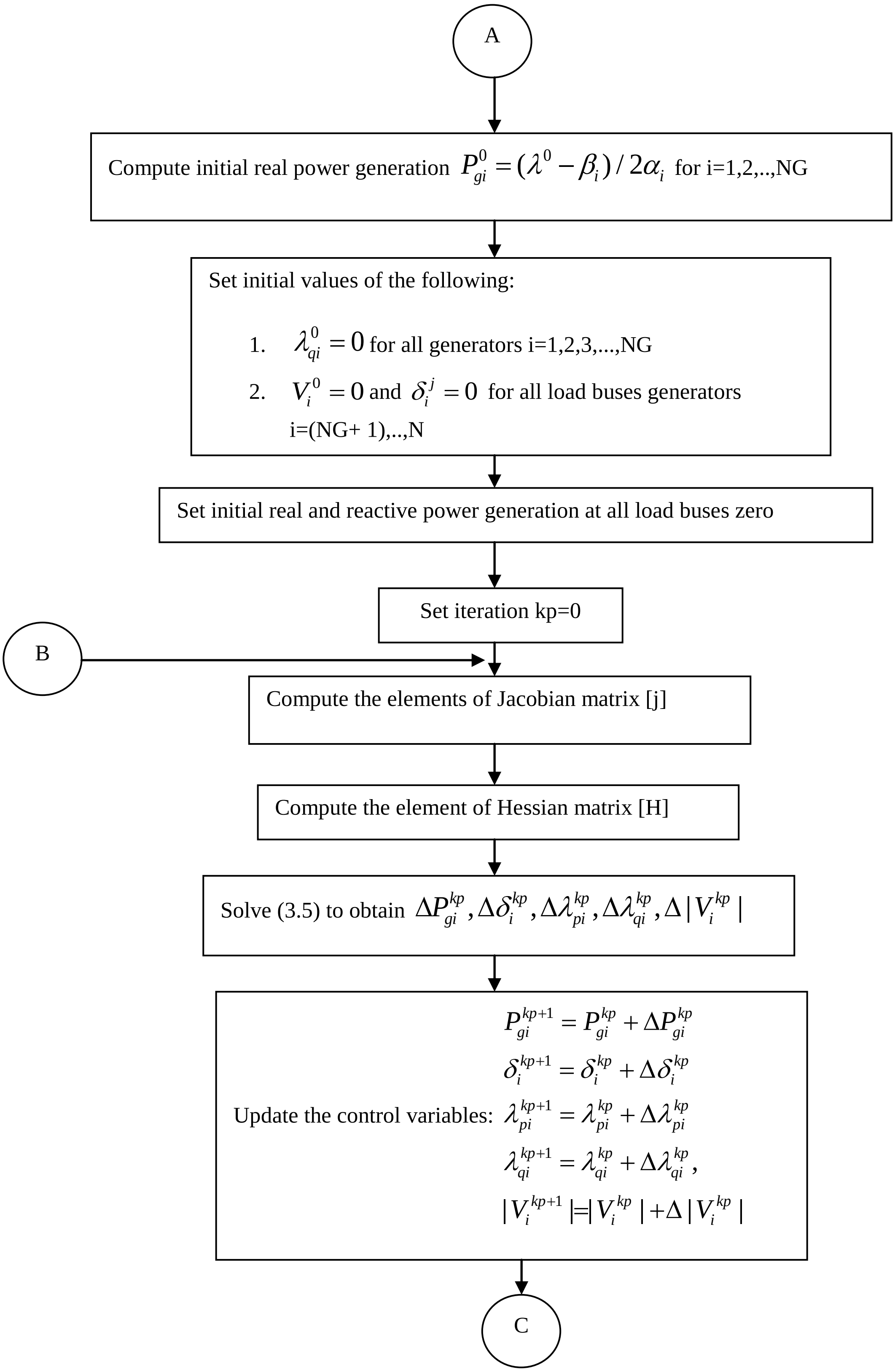
Or,

$$\begin{bmatrix} H_{P_g P_g} & 0 & H_{P_g\lambda_P} & 0 & 0 \\ 0 & H_{\delta\delta} & H_{\delta\lambda_P} & H_{\delta\lambda_q} & H_{\delta|V|} \\ H_{\lambda_p P_g} & H_{\lambda_p\delta} & 0 & 0 & H_{\lambda_p|V|} \\ 0 & H_{|V|\delta} & H_{|V|\lambda_P} & H_{|V|\lambda_q} & H_{|V||V|} \\ 0 & H_{\lambda_P\delta} & 0 & 0 & H_{\lambda_P|V|} \end{bmatrix} \begin{bmatrix} \Delta P_{g_i} \\ \Delta\delta_i \\ \Delta\lambda_{p_i} \\ \Delta\lambda_{q_i} \\ \Delta|V_i| \end{bmatrix} = \begin{bmatrix} J_{P_{g_i}} \\ J_{\delta_i} \\ J_{\lambda_{p_i}} \\ J_{|V_i|} \\ J_{\lambda_{q_i}} \end{bmatrix} \qquad (3.43)$$

Where H & J are called *Hesseian* and *Jacobian Matrices* , respectively.

The flow-chart for solution of optimal power flow problem using *Newton – Raphson* method is shown in Figure 3.1


Start
Read bus data of the system and form [Y_{bus}] matrix
Read ,
1. Tolerance allowed, ε and maximum number of iteration allowed, *KPMAX*
2. Total No. of generators, NG, total Number of buses N
3. α_i , β_i, γ_i, for each generator, i.e for i=1,2,3,…,NG
Read the following for each bus (i.e. for i=1,2,3,…,NG
Initial bus voltage magnitude, initial load angel; Real Load; Reactive Load
Total real load $P_{load} = \sum_{i=1}^{N} P_{load_i}$
Separate real and imaginary parts of the admittance matrix Y
$G_{ij} = \mathrm{Real}(Y_{ij}), B_{ij} = \mathrm{Im}(Y_{ij})$ for i=1,2,3,…,N & j=1,2,3,..,N
Fix generator bus voltage magnitude and angle for KPMAX number of iteration,
$V_i^j = V_i^0, and\ \delta_i^j = \delta_i^0$ for i=1,2,3,…,NG & j=1,2,3,..,KPMAX
Compute initial of $\lambda_{pi}, \lambda_{pi}{}^0 = \left[P_{Load_T} + \left(\sum_{i=1}^{NG} \frac{\beta_i}{2\alpha_i} \right) \Big/ \left(\sum_{i=1}^{NG} \frac{1}{2\alpha_i} \right)^{-1} \right]$ for all generators
A


A
Compute initial real power generation $P_{gi}^{0} = (\lambda^{0} - \beta_i)/2\alpha_i$ for i=1,2,..,NG
Set initial values of the following:
1. $\lambda_{qi}^{0} = 0$ for all generators i=1,2,3,...,NG
2. $V_i^{0} = 0$ and $\delta_i^{j} = 0$ for all load buses generators i=(NG+ 1),..,N
Set initial real and reactive power generation at all load buses zero
Set iteration kp=0
B
Compute the elements of Jacobian matrix [j]
Compute the element of Hessian matrix [H]
Solve (3.5) to obtain $\Delta P_{gi}^{kp}, \Delta\delta_i^{kp}, \Delta\lambda_{pi}^{kp}, \Delta\lambda_{qi}^{kp}, \Delta|V_i^{kp}|$
Update the control variables:
$P_{gi}^{kp+1} = P_{gi}^{kp} + \Delta P_{gi}^{kp}$
$\delta_i^{kp+1} = \delta_i^{kp} + \Delta\delta_i^{kp}$
$\lambda_{pi}^{kp+1} = \lambda_{pi}^{kp} + \Delta\lambda_{pi}^{kp}$
$\lambda_{qi}^{kp+1} = \lambda_{qi}^{kp} + \Delta\lambda_{qi}^{kp}$,
$|V_i^{kp+1}| = |V_i^{kp}| + \Delta|V_i^{kp}|$
C

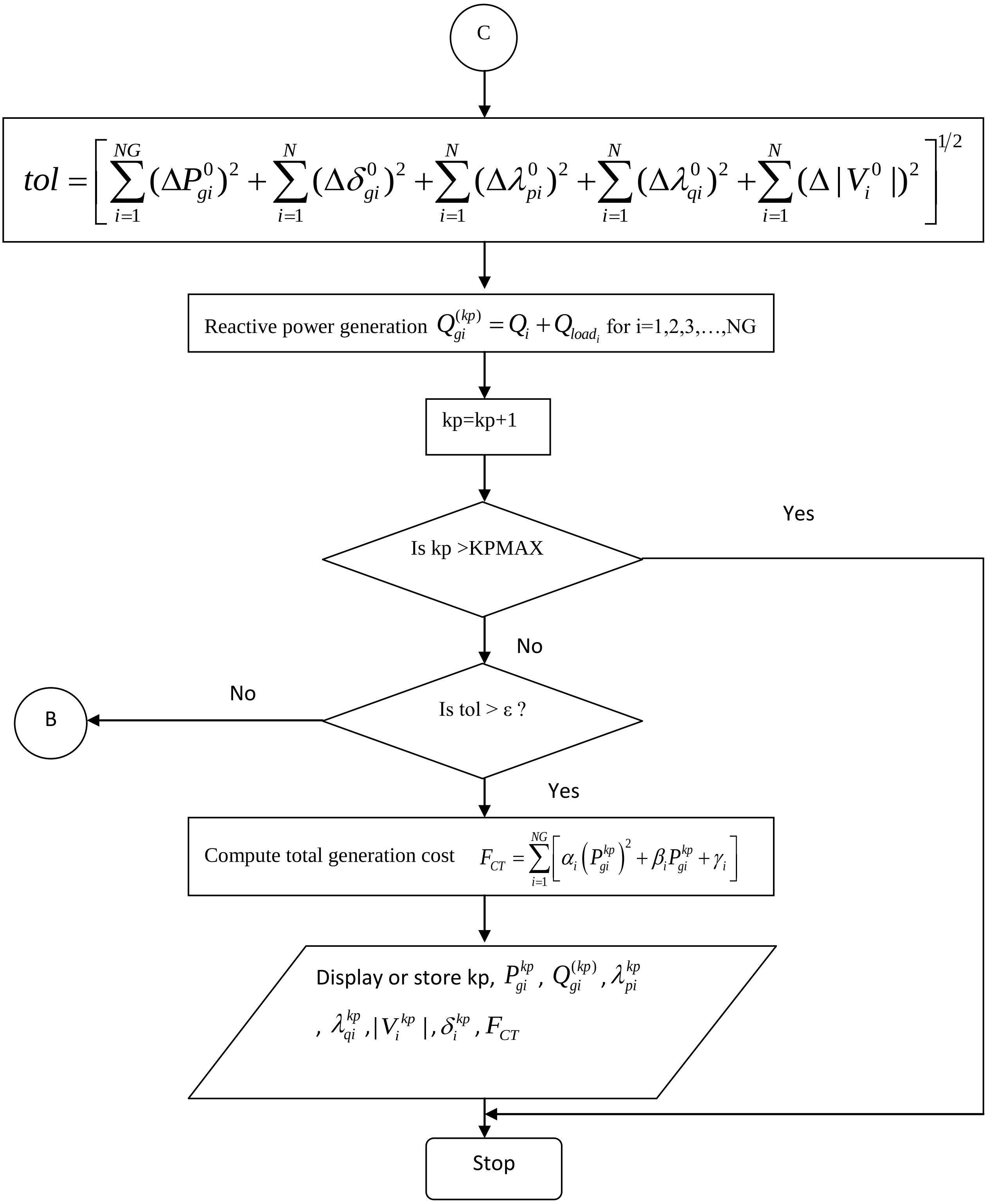


Figure 3.1 Flow-chart To Find Optimal Power Flow Solution Using Newton Raphson Method.

3.3 Intelligent Methods

To overcome the limitations and deficiencies in analytical methods, ***intelligent methods*** based on ***Artificial Intelligence*** (AI) techniques have been developed in the recent past. These methods can be classified or divided into the following,

a) Artificial Neural Networks (ANN)

b) Genetic Algorithms (GA)

c) Particle Swarm Optimization (PSO)

d) Ant Colony Algorithm

The major advantage of the intelligent methods is that they are relatively versatile for handling various qualitative constraints. These methods can find multiple optimal solutions in single simulation run. So they are quite suitable in solving multi objective optimization problems. In most cases, they can find the global optimum solution. The main advantages of intelligent methods are: Possesses learning ability, fast, appropriate for non-linear modeling, etc. whereas, large dimensionality and the choice of training methodology are some disadvantages of intelligent methods.

For the intelligent method *Particle Swarm Optimization* was considered to find the optimal power flow for IEEE 39 New England test system for comparison with the conventional method.

3.3.1 Particle Swarm Optimization:

Particle swarm optimization (PSO) is a population based evolutionary computation technique inspired from the social behaviors of bird flocking or fish schooling. Since its invention in 1995 by Kennedy and Eberhart, PSO has become one of the most popular methods applied to various optimization problems due to its simplicity and capability to find near optimal solutions. In conventional PSO, a population of particles moves in the search space of a problem to approach the global optimum. Figure 3.2 and Figure 3.4 shows the nature of PSO method:

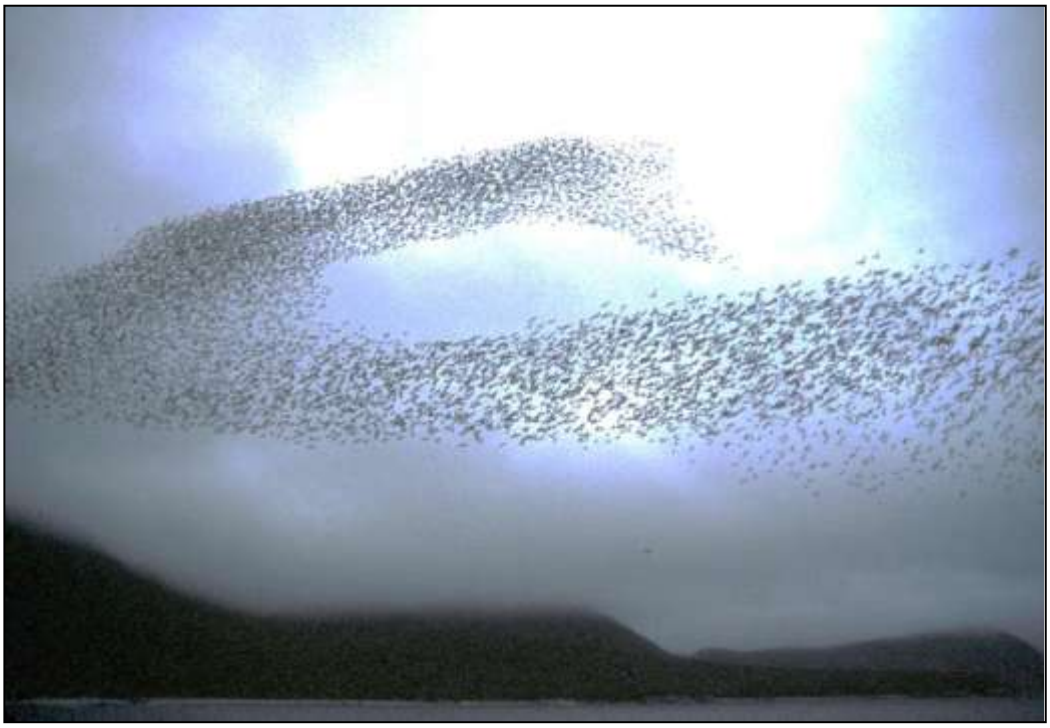


Figure 3.2: Example on the flock of bird in nature

Figure 3.3: example of school of fish in nature

The movement of each particle in the population is determined via its location and velocity. During the movement, the velocity of each particle is changed over time and its position is updated accordingly [4].

Consider an *n*-dimensional optimization problem:

Min *f(p)*

where *p* = [*p1*, *p2*, …, *pn*] is a vector of variables.

For implementation to the problem, the position and velocity vectors of particle *d* are represented by

$p_d = [p_{1d}, p_{2d}, \ldots, p_{nd}]$ and

$v_d = [v_{1d}, v_{2d}, \ldots, v_{nd}]$, respectively,

Where $d = 1,\ldots, NP$ and *NP* is the number of particles.

The best previous position of particle *d* is based on the valuation of the fitness function represented by $pbest_d = [p_{1d}, p_{2d}, \ldots, p_{nd}]$ and the best particle among all particles represented by *gbest*. The velocity and position of each particle in the next iteration (*k*+1) for fitness function evaluation are calculated as follows:

$$v_{id}^{(k+1)} = w^{(k+1)} * v_{id}^{k} + C_1 * rand_1 * (pbest_{id}^{(k)} - p_{id}^{(k)}) + C_2 * rand_2 * (gbest_i^{(k)} - p_{id}^{(k)}) \quad (3.6)$$

$$p_{id}^{(k+1)} = p_{id}^{(k)} + v_{id}^{(k+1)} \quad (3.7)$$

Where *w* is the inertia weight factor, C_1 and C_2 are cognitive and social parameters, respectively, and $rand_1$ and $rand_2$ are random values in [0, 1].

In conventional PSO, the inertia weight factor and cognitive and social parameters are constants. Position and velocity of each particle have their own limits. Regarding position limits, the lower and upper bounds are defined by the limits of variables represented by the particle's position. However, the velocity limits for the particles can be defined by the user. Generally, the solution quality of PSO is sensitive to cognitive and social parameters and velocity limits for particles.

The inertia weight factor linearly declines from its maximum to the minimum value as the number of iterations increases from 0 to *ITmax*. The inertia weight factor at iteration *k* is updated as follows:

$$w^{(k)} = w_{\max} - (w_{\max} - w_{\min}) \frac{k}{IT_{\max}} \quad (3.8)$$

Where w_{max} and w_{min} are maximum and minimum weight factor, respectively, and *ITmax* is the maximum number of iterations.

3.3.1.1 Application of PSO Method to Economic Load Dispatch:

Steps of Implementation:

1. Initialize the Fitness Function, i.e. Total cost function from the individual cost function of the various generating stations.
2. Initialize the PSO parameters Population size, C_1, C_2, W_{max}, W_{min}, error gradient etc.
3. Input the Fuel cost Functions, MW limits of the generating stations along with the B-coefficient matrix and the total power demand.
4. at the first steps of the execution of the program a large No. (equal to the population size) of vectors of active power satisfying the MW limits are randomly allocated.
5. For each vector of active power the value of the fitness function is calculated. All values obtained in iteration are compared to obtain Pbest. At each iteration all values of the whole population till then are compared to obtain the Gbest. At each step these values are updated.
6. At each step error gradient is checked and the value of Gbest is plotted till it comes within the pre-specified range.
7. This final value of Gbest is the minimum cost and the active power vector represents the economic load dispatch solution.

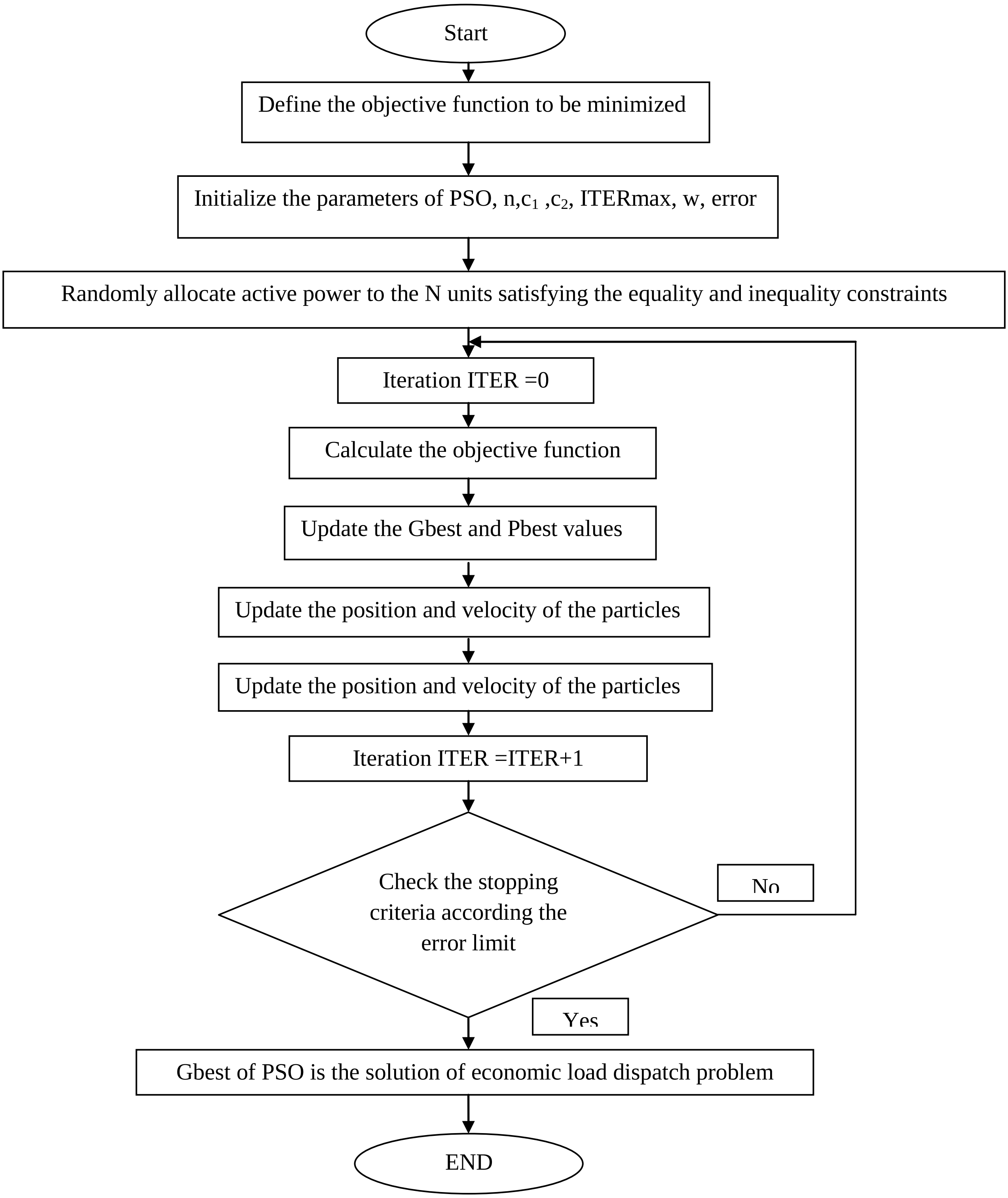


Figure 3.4 Flow-chart To Find Optimal Power Flow Solution Using Particle Swarm Optimization Method.

3.3.1.2 The Advantages and Disadvantages of Using PSO

- ***Advantages***

  1. PSO is easy to implement the coding.
  2. PSO is able to produce high quality solutions by using less time.
  3. PSO is less sensitive to the objective function compared to conventional mathematical methods.
  4. PSO has less negative impact toward the solutions.
  5. PSO is less divergence.
  6. PSO has less parameter to control.

- ***Disadvantages***

  1. PSO need a longer computation time compared to the mathematical methods.
  2. PSO need more iteration than the classical method.

4.1 Case study:

For the case study IEEE 39 New England test system was used. This system consists of 10 generators units, 39 buses and 46 transmissions line the single line diagram of the system is shown in Figure 4.1 the line and bus data is shown in Appendix A.

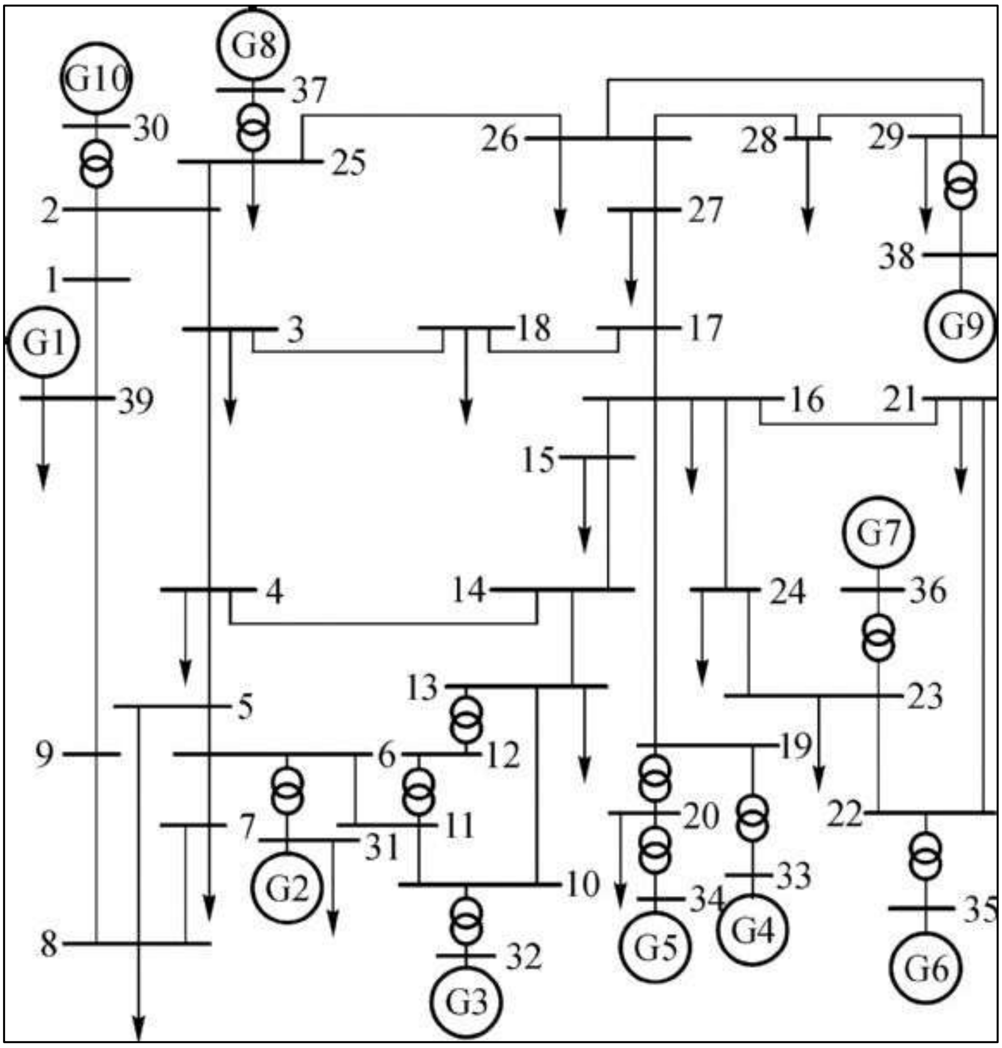


Figure 4.1: Single line diagram of the IEEE 39 New England test system

4.2 Result of the MATLAB Program:

The simulation had been carried out on the case study using NR and PSO methods the analysis had been done to the results.

4.2.1 Result with Newton Raphson Method:

The Newton Raphson method was implemented in MATLAB; the result is shown in Table 4.1.

After applying The MATLAB program the below results was found:

- The total Demand for both cases is 6150.130 MW.
- The generation Error is zero (power generation-load –losses=0).
- The power loss had been calculated and had been found to be equal to 63.11 MW.
- The optimal power generation is calculated by using Newton Raphson Method for the optimal power flow the program as shown in Table 4.1

Table 4.1 Newton Raphson MATLAB Result

Unit No	***Real Power Generation (MW)***	***Generation Cost ($/hr)***
G1	299.00	14,737.58
G2	439.59	22,123.85
G3	497.11	24,960.67
G4	572.51	29,281.60
G5	498.31	25,117.13
G6	673.71	33,648.63
G7	620.00	27,430.78
G8	643.00	25,033.85
G9	920.00	42,286.85
G10	1,050.00	51,140.10
Total	6,213.24	295,761.01
Power Loss (MW)	63.11	

4.2.2 Result with Particle swarm optimization Method:

The Particle swarm optimization method was implemented in the MATLAB program the result is shown in Table 4.2. In the PSO analysis the number of particles was set to 100. Besides, the weight factor was between the ranges of 0.4 to 0.9. When weight factor was set from 0.4 to 0.9, the PSO was able to search for larger space and discover the Gbest using shortest time. The constants and was set to be 2. Then, the number of iteration was set as 100000 iterations to avoid the analysis complete before it was really done the iteration. Error was set as 1e-06, so if the error was less than this value, the iteration process will terminate after 5000 iterations. During the analysis, the B-coefficient was considered to calculate the losses in transmission line for more accurate result. Besides, the generators power limit constraint was also involved in the analysis.

Table 4.2 Particle Swarm Optimization MATLAB Result

Unit No	***Real Power Generation (MW)***	***Generation Cost($/hr)***
G1	353.77	18,845.4996
G2	445.19	22,564.3987
G3	485.24	24,015.3960
G4	540.78	26,717.6073
G5	477.83	23,471.5681
G6	693.75	35,213.1706
G7	620.00	27,430.7719
G8	643.00	25,033.8461
G9	920.00	42,286.8480
G10	1,011.39	48,038.6893
Total	6,190.95	293,617.7956
Power loss (MW)	39.10	

4.3 Discussion:

Comparing results of the two methods, the generation Cost, total Real power Generation and Power loss is less in PSO method than NR method as shown in Table 4.3.

Table 4.3 Comparison between NR & PSO Results

Methods / Area Of discussion	Newton Raphson Method	Particle swarm optimization	Difference
Total Real power Generation (MW)	6,213.24	6,190.95	22.29 (MW)
Total Generation Cost ($/hr)	295,761.01	293,617.7956	2,143.2144($/hr)
Power Losses (MW)	63.11	39.10	24.01(MW)

Table 4.3 shows a comparison between Newton Raphson and Particle Swarm Optimization result in the 10 generators units and 39 bus systems, it was found that Particle Swarm Optimization was able to produce the lower generation cost. Besides, the transmission losses in Particle Swarm Optimization were also lower than Newton Raphson method, dispatches of output power for each generator was different for both methods. However, Newton Raphson method was used less computational time compared to Particle Swarm Optimization. It was faster in the iteration process.

Finally, it can be concluded that Particle Swarm Optimization method was more suitable to be used in solving the economic dispatch problem as it could produce lower generation cost while satisfying the power demand. In the purpose of cost saving and environmental problem, Particle Swarm Optimization had done better contribution. Thus, PSO method was superior compared to Newton Raphson method.

As shown in Figure 4.2 the difference between Real Power Generation for each unit to the two methods.

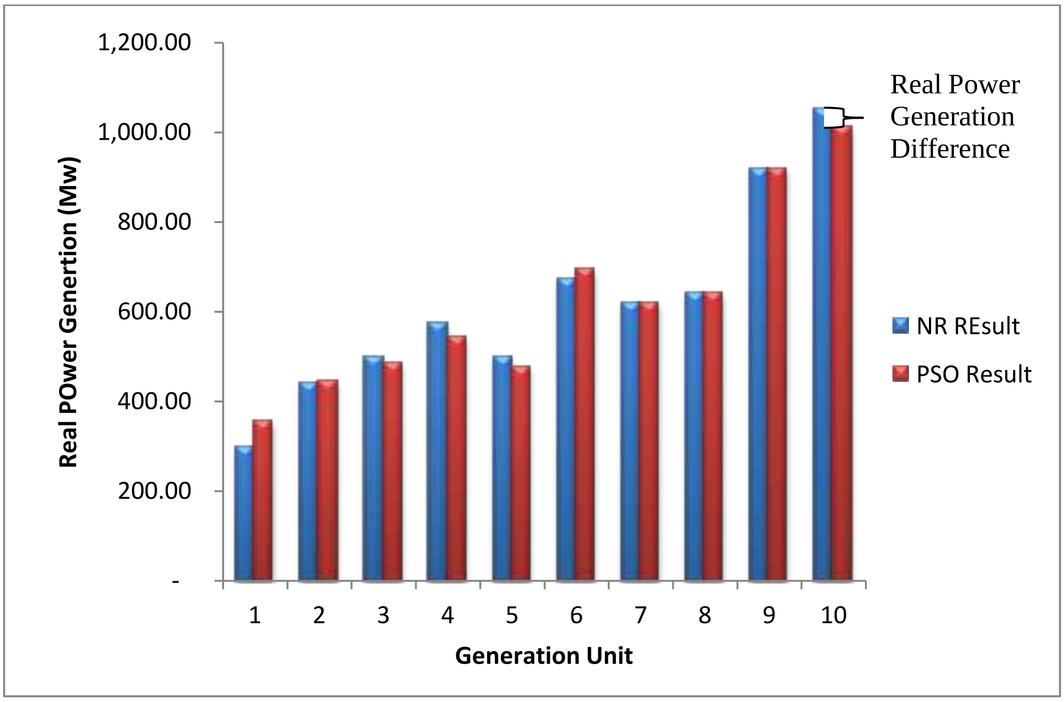


Figure 4.2 Differences between Real Power Generations (Mw)

The difference between the Generation Cost ($/hr) for NR and PSO Methods is shown in Figure 4.3.

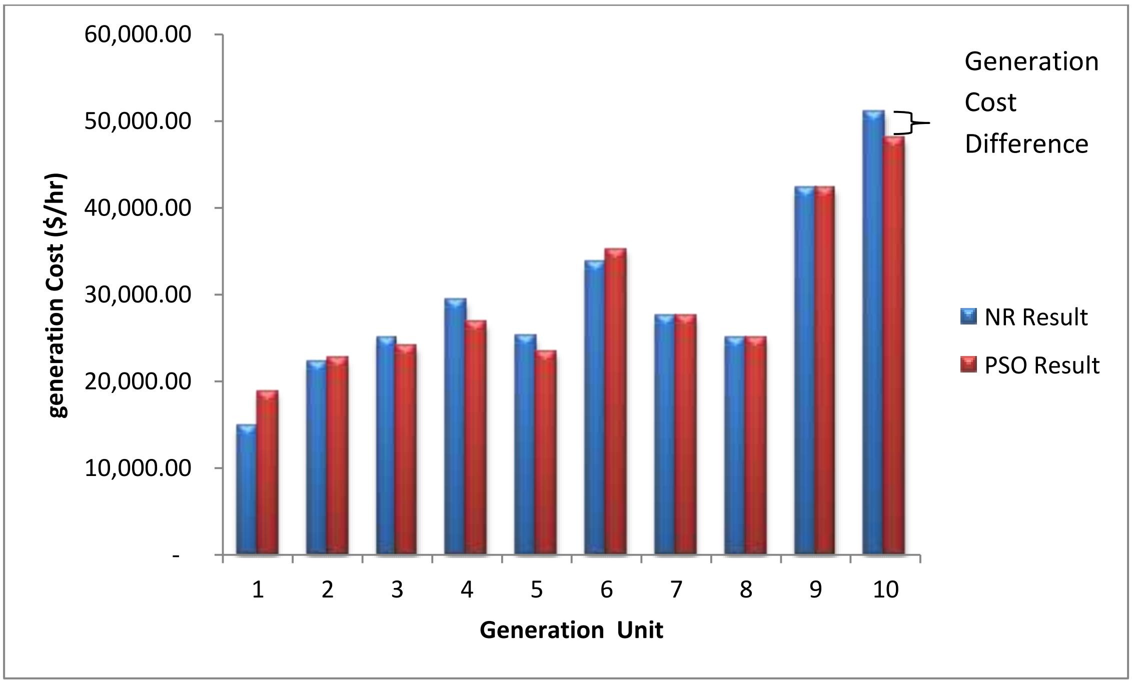


Figure 4.3 Differences Between Generation Cost ($/hr)

5.1 CONCLUSION

The main purpose of this thesis was due to the importance of economic dispatch in the power system. Economic load dispatch in electric power sector is an important task, as it is required to supply the power at the minimum cost which aids in profit-making. As the efficiency of newly added generating units are more than the previous units the economic load dispatch has to be efficiently solved for minimizing the cost of the generated power.

From the analysis of IEEE 39 New England test system it was found that Particle Swarm Optimization method was able to produce a better fuel cost compared to the Newton Raphson method. For the same power demand, Particle Swarm Optimization was able to produce less cost than NR. Besides, the losses produced by PSO for the same power demand according to the B-coefficient was smaller than NR produced. As we know, higher losses will result in the consumption in fuel and increase the fuel cost. Thus, it was very important to get the optimal dispatch in reducing losses. The Real Power Generation and Generation cost of the particle swarm optimization result was close to that of the NR (conventional method) but tends to give a better solution in case of higher order systems.

Per to the MATLAB result, Newton Raphson was using less computational time in the analysis compared to PSO method. The computational time of NR method was not affected by the increasing of number of generators. However, the computational time of the PSO method will be increased due to the increment of generator amount. Although, PSO was using more time in analyzing the result, it produces better result than the NR method. PSO was also possessed steady convergence characteristic which result in accuracy and consistency in the result.

The B-coefficient was obtained through the Matlab by applying the Bloss program to the Bus data and line data of the test system were required by the

Bloss program to generate the B-coefficient. By solving the load flow analysis, it was able to generate the B-coefficient matrix of the system that we used in solving ED problem with PSO Method.

5.2 RECOMMENDATION

- PSO algorithm can be combined with other simple optimization techniques to improve their performance when applied to economic load dispatch problems and obtain better results.
- For the PSO Method; Bus data and line data of the system can be taken as input along with the load demand to obtain the minimization function with constraints on voltage and reactive power at various points of the system.
- Software beside MATLAB may be introduced if it is able to be applied in solving the ED problem.
- This work may be extended for new optimization techniques, this may be used to compare and find out the better optimization technique.
- PSO algorithm can be combined with other simple optimization techniques to improve their performance when applied to ELD problems and obtain better results.
- ED problem was formulated as economic cost dispatch (ELD), but further, Existence of Emission Dispatch (EMD) leads to the formulation of Combined Emission Economic Dispatch (CEED) and emission Controlled Economic Dispatch (ECED) problem formulation. In future this problem could be solved as individual optimization of these two contradictory objectives.

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APPENDIX A

Bus data and line data:

For our study in IEEE 39 New England bus system we will use the parameter of bus data as shown in Table A.1 and line data at Table A.2 to compute the optimal economic dispatch for the case study.

Table A.1: 39 New England Bus data

Bus No.	***P Generation (MW)***	***Q Generation (MVAR)***	***P Load (MW)***	***Q Load (MVAR)***	***Bus Type****
1	0.00	0.00	0.00	0.00	0
2	0.00	0.00	0.00	0.00	0
3	0.00	0.00	322	2.5	0
4	0.00	0.00	500	184	0
5	0.00	0.00	0.00	0.00	0
6	0.00	0.00	0.00	0.00	0
7	0.00	0.00	233.8	84	0
8	0.00	0.00	522	176.6	0
9	0.00	0.00	0.00	0.00	0
10	0.00	0.00	0.00	0.00	0
11	0.00	0.00	0.00	0.00	0
12	0.00	0.00	8.53	88	0
13	0.00	0.00	0.00	0.00	0
14	0.00	0.00	0.00	0.00	0
15	0.00	0.00	320	153	0
16	0.00	0.00	329	32.3	0
17	0.00	0.00	0.00	0.00	0

18	0.00	0.00	158	30	0
19	0.00	0.00	0.00	0.00	0
20	0.00	0.00	680	103	0
21	0.00	0.00	274	115	0
22	0.00	0.00	0.00	0.00	0
23	0.00	0.00	247.5	84.6	0
24	0.00	0.00	308.6	-92.2	0
25	0.00	0.00	224	47.2	0
26	0.00	0.00	139	17	0
27	0.00	0.00	281	75.5	0
28	0.00	0.00	206	27.6	0
29	0.00	0.00	283.5	26.9	0
30	161	400	0.00	250	2
31	677.871	0.00	9.2	4.6	2
32	650	206.965	0.00	0.00	2
33	632	108.293	0.00	0.00	2
34	508	166.688	0.00	0.00	2
35	650	210.661	0.00	0.00	2
36	560	100.165	0.00	0.00	2
37	540	-1.36945	0.00	0.00	2
38	830	21.7327	0.00	0.00	2
39	0.00	0.00	1104	250	1

*Bus Type: (1) slack bus, (2) generator bus (PV bus), and (0) load bus (PQ bus)

Table A.2: 39 New England Line Data.

From Bus	***To Bus***	***Resistance (p.u.)***	***Reactance (p.u.)***	***Line charging admittance (p.u.)***	***Tap ratio***
1	2	0.0035	0.0411	0.6987	1
1	39	0.001	0.025	0.75	1
2	3	0.0013	0.0151	0.2572	1
2	25	0.007	0.0086	0.146	1
2	30	0.0	0.0181	0.00	1.025
3	4	0.0013	0.0213	0.2214	1
3	18	0.0011	0.0133	0.2138	1
4	5	0.0008	0.0128	0.1342	1
4	14	0.0008	0.0129	0.1382	1
5	6	0.0002	0.0026	0.0434	1
5	8	0.0008	0.0112	0.1476	1
6	7	0.0006	0.0092	0.113	1
6	11	0.0007	0.0082	0.1389	1
6	31	0.00	0.025	0.00	1.07
7	8	0.0004	0.0046	0.078	1
8	9	0.0023	0.0363	0.3804	1
9	39	0.001	0.025	1.2	1
10	11	0.0004	0.0043	0.0729	1
10	13	0.0004	0.0043	0.0729	1
10	32	0.00	0.02	0.00	1.07
12	11	0.0016	0.0435	0.00	1.006
12	13	0.0016	0.0435	0.00	1.006
13	14	0.0009	0.0101	0.1723	1
14	15	0.0018	0.0217	0.366	1

15	16	0.0009	0.0094	0.171	1
16	17	0.0007	0.0089	0.1342	1
16	19	0.0016	0.0195	0.304	1
16	21	0.0008	0.0135	0.2548	1
16	24	0.0003	0.0059	0.068	1
17	18	0.0007	0.0082	0.1319	1
17	27	0.0013	0.0173	0.3216	1
19	20	0.0007	0.0138	0.00	1.06
19	33	0.0007	0.0142	0.00	1.07
20	34	0.0009	0.018	0.00	1.009
21	22	0.0008	0.014	0.2565	1
22	23	0.0006	0.0096	0.1846	1
22	35	0.00	0.0143	0.00	1.025
23	24	0.0022	0.035	0.361	1
23	36	0.0005	0.0272	0.00	1
25	26	0.0032	0.0323	0.531	1
25	37	0.0006	0.0232	0.00	1.025
26	27	0.0014	0.0147	0.2396	1
26	28	0.0043	0.0474	0.7802	1
26	29	0.0057	0.0625	1.029	1
28	29	0.0014	0.0151	0.249	1
29	38	0.0008	0.0156	0.00	1.025

Table A.3: 39 New England Characteristic of Power Generators:

unit	***a*** ***($/MW^{2}hr)***	***b*** ***($/MWhr)***	***c*** ***($/hr)***	***Pmax*** ***(MW)***	***Pmin*** ***(MW)***
1	0.03720	26.4408	180	360	155
2	0.03256	21.0771	275	680	320
3	0.03102	18.6626	352	718	323
4	0.02871	16.8894	792	680	275
5	0.03223	17.3998	440	600	230
6	0.02064	21.6180	348	748	350
7	0.02268	15.1716	588	620	220
8	0.01776	14.5632	984	643	225
9	0.01644	14.3448	1260	920	350
10	0.01620	13.5420	1200	1050	450