DYNAMIC ECONOMIC DISPATCH USING PARTICLE SWARM OPTIMIZATION

Thesis submitted in partial fulfillment of the requirements for the award

of degree of

Master of Engineering

in

Power Systems & Electric Drives

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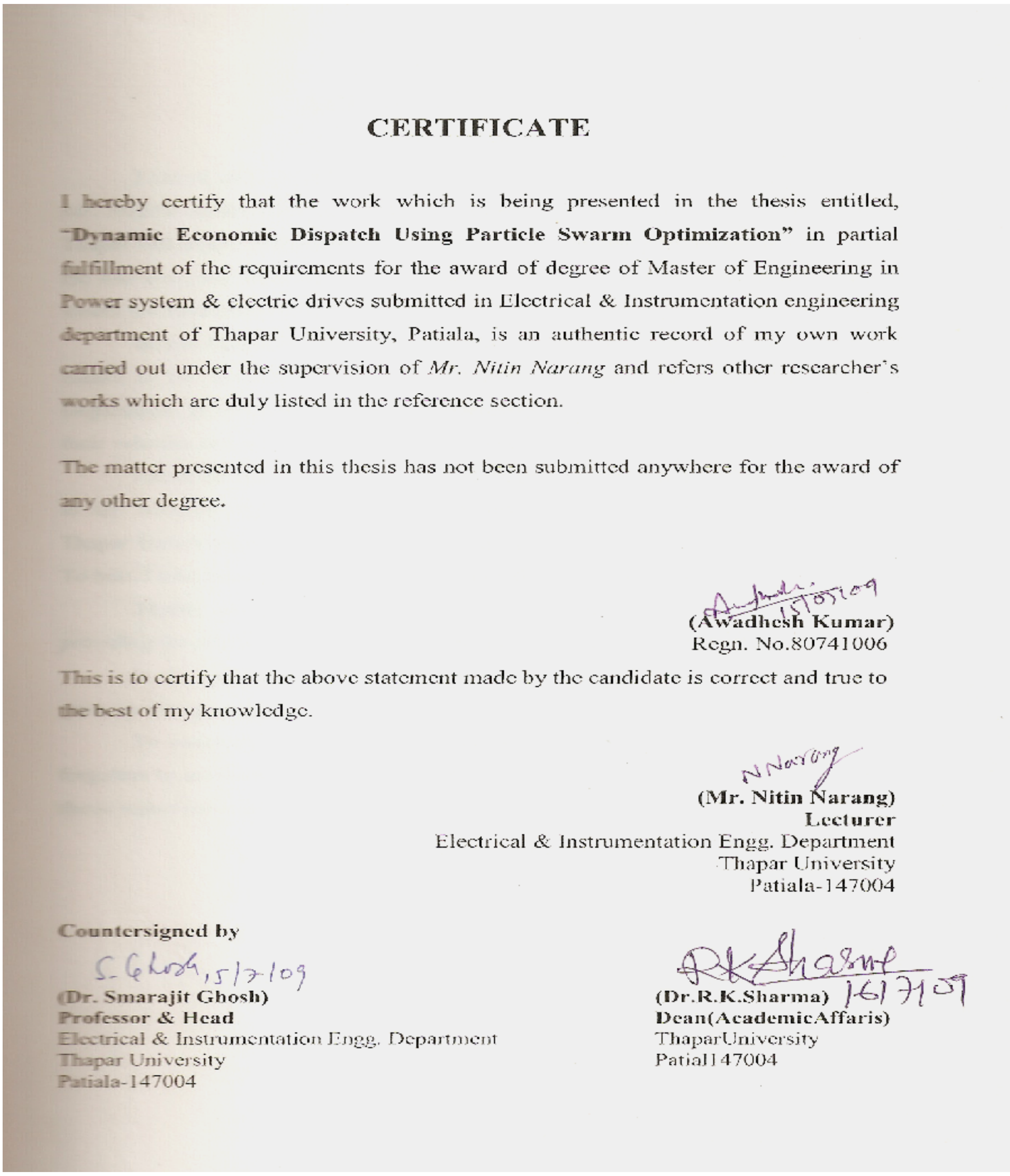

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "**Dynamic Economic Dispatch Using Particle Swarm Optimization**" in partial fulfillment of the requirements for the award of degree of Master of Engineering in Power system & electric drives submitted in Electrical & Instrumentation engineering department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Mr. Nitin Narang* and refers other researcher's works which are duly listed in the reference section.

The matter presented in this thesis has not been submitted anywhere for the award of any other degree.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ABSTRACT

The power utility needs to ensure that the electrical power is generated with minimum cost. Hence, for economic operation of the system, the total demand must be appropriately shared among the generating units with an objective to minimize the total generation cost for the system. Thus, Economic dispatch (ED) is one of the important problem of power system operation and control.

Dynamic economic dispatch (DED) based on particle swarm optimization technique for the determination of the global or near global optimum dispatch solution including satisfied all the constraints. PSO has been successfully applied to various fields of power system optimization. It determines the optimal operation of units with load demands over a certain period of time with an objective to minimize total production cost.

In this thesis, an attempt is made to solve an economic dispatch problem using PSO technique. A general PSO based dynamic economic dispatch algorithm has been developed which is tested for five generator unit and 12 hours operation. Further, the marginal limit of generation for each generator unit at define hour is also calculated.

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CHAPTER # 1

INTRODUCTION

1.1ECONOMIC DISPATCH

"Economic dispatch" has a common, general meaning – the practice of operating a coordinated system so that the lowest-cost generators are used as much as possible to meet demand, with more expensive generators brought into production as loads increase (and conversely, more expensive generation eliminated from production as load falls). EPAct's definition of economic dispatch –"the operation of generation facilities to produce energy at the lowest cost to reliably serve consumers, recognizing any operational limits of generation and transmission facilities".

1.1.1 OBJECTIVE FUNCTIONS

The main aim of electric supply utility has been identified as to provide the smooth electrical energy to the consumers. While doing so, it should be ensured that the electrical power is generated with minimum cost. Hence in order to achieve an economic operation of the system, the total demand must be appropriately shared among the units. This will minimize the total generation cost for the system with the voltage level maintained at the safe operating limits. Major considerations to fulfilling the objective are

- Loss minimization
- Fuel cost minimization
- Profit maximization (fuel costs/load tariffs)

1.2 LITERATURE REVIEW

Economic dispatch had been done by Happ H.H. in 1974 which reviewed the progress of economic dispatch going as far back as the early 1920's [51], when engineers were concerned with the problem of economic allocation of generation or the proper division of the load among the generating units available. Prior to 1930, various methods are in use such as the base load method where the next most efficient unit is loaded to its maximum capability, then the second most efficient unit is loaded, etc. And then "best point loading," where units are successively loaded to their lowest heat rate point, beginning with the most efficient unit and working down to the least efficient unit [18].

Feng Gao has presented [52] economic dispatch algorithms for thermal unit system involving combined cycle units. The economic dispatch (ED) function allocates total demand among the available generating units to minimize the total generation cost. Cost curves of conventional thermal units can be modelled as convex functions. Equal incremental cost is criteria to solve the traditional ED problem. Economic dispatch involving combined cycle units is a non-convex optimization that cannot be handled by traditional equal incremental cost criterion. The techniques considered include Genetic Algorithm (GA) and a proposed Hybrid Technique (HT). This hybrid technique is not only feasible but it is also relatively fast to find ED solution for thermal unit system including combined cycle units.

D. Walters and G.B. Sheble have presented genetic algorithm solution of economic dispatch with valve point loading [22]. A genetics-based algorithm is used to solve an economic dispatch problem for valve point discontinuities. The algorithm utilizes payoff information of candidate solutions to evaluate their optimality. Thus, the constraints of classical Lagrangian techniques on unit curves are circumvented. The formulations of an economic dispatch computer program using genetic algorithms are presented and the program's performance using two different encoding techniques is compared. The results are verified for a sample problem using a dynamic programming technique [11, 38].

Amir Mohammadi, Mohammad Hadi Varahram, Iraj Kheirizad have presented [48] online solving of economic dispatch problem using neural network approach and comparing it with classical method. In this study, two methods for solving economic dispatch problems, namely Hopfield neural network and iteration method are compared. Three sample of power system with 3, 6 and 20 units have been considered. The time required for CPU, for solving economic dispatch of these two systems has been calculated. It has been shown that for on-line economic dispatch, Hopfield neural network is more efficient and the time required for convergence is considerably smaller compared to classical methods [38].

Kit Po Wong has presented [49] the computational intelligence (CI) methods include techniques in artificial intelligence, fuzzy logic, artificial neural networks and evolutionary computation [8]. These methods concentrates on the recent development of (a) artificial-intelligent-based approach, (b) evolutionary-programming based economic dispatch and (c) genetic-algorithm-based economic dispatch method. For the area in (a), artificial-intelligent-based learning ability will be described. An improved evolutionary programming method for economic dispatch will be presented for the area in (b).

J.C. Silva Chávez have presented a parallel population repair genetic algorithm for power economic dispatch. In the present work Power Economic Dispatch (ED) technique based on Genetic Algorithms (GA) is presented. The ED with GAs is developed based on real-valued codification. In the developed methodology only the cost function is evaluated and a global minimum solution is computed, independently of the cost function type. In order to achieve this solution, a novel strategy based on the energy conservative space concept [23, 12].

Particle Swarm Optimization (PSO) is a population-based optimization method first proposed by Kennedy and Eberhart [10, 13]. In order to find an optimal or near optimal solution to the problem, PSO updates the current generation of particles (each particle is a candidate solution to the problem) using the information about the best solution obtained by each particle and the entire population. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous non-linear optimization problems [10-12]. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods. Although the PSO seems to be sensitive to the tuning of some weights or parameters, many researchers are still in progress for proving its potential in solving complex power system problems.

1.3 AUTHOR CONTRIBUTION

Economic dispatch benefits electricity users to minimizing the cost of electricity. By systematically seeking the lowest cost of energy production consistent with electricity demand, economic dispatch reduces total electricity costs. To minimize costs, economic dispatch typically increases the use of the more efficient generation units, which can lead to better fuel utilization, lower fuel usage than would result from using less-efficient generation. Economic dispatch methods are also flexible enough to incorporate policy goals such as promoting fuel diversity or respecting demand as well as supply resources. Over the long term, economic dispatch can encourage new investment in generation as well as in transmission expansion and upgrades that enhance both reliability and cost savings.

Here, in the thesis PSO based dynamic economic dispatch method has been reported and it has been shown that the algorithm is capable of finding the global or near global optimum solutions for large optimization problems. This thesis presents DED (dynamic economic dispatch) algorithm based on PSO (particle swarm optimization) technique for the determination of the best optimum dispatch solution.

1.4 ORGANIZATION OF THE THESIS

The work carried out has been summarized in six chapters. The Chapter 1 highlights the brief introduction of economic dispatch and, literature survey of the related topics of the problem. This chapter also includes the objective of the thesis.

The Chapter 2 briefly describes methods of solving economic dispatch using various methods, and also discusses thermal system dispatching with network losses considered.

The Chapter 3 discusses the brief introduction of PSO and how to select the parameter in particle swarm optimization. To ensure convergence of PSO adjustments of various parameters need to be carefully adjusted.

The Chapter 4 explains the problem formulation of the topic. The step-wise procedure to solve the dynamic economic dispatch problem is presented.

The Chapter 5 details the results pertaining dynamic economic dispatch using particle swarm optimization.

Chapter 6 will conclude with a summary, scope of future work of economic dispatch.

CHAPTER # 2

ECONOMIC DISPATCH

2.1 ECONOMIC DISPATCH

A major challenge for all power utilities is to not only satisfy the consumer demand for power, but to do so at minimal cost. Any given power system can be comprised of multiple generating stations, each of which has its own characteristic operating parameters. The cost of operating these generators does not usually correlate proportionally with their outputs; therefore the challenge for power utilities is to try to balance the total load among generators that are running as efficiently as possible [28, 31].

In a typical power system, multiple generators are implemented to provide enough total output to satisfy a given total consumer demand [6]. Each of these generating stations can, and usually does, have a unique cost-per-hour characteristic for its output operating range. A station has incremental operating costs for fuel and maintenance; and fixed costs associated with the station itself that can be quite considerable in the case of a nuclear power plant, for example. Things get even more complicated when utilities try to account for transmission line losses, and the seasonal changes associated with hydroelectric plants.

The main aim of electric supply utility has been identified as to provide the smooth electrical energy to the consumers. While doing so, it should be ensured that the electrical power is generated with minimum cost. Hence in order to achieve an economic operation of the system, the total demand must be appropriately shared among the units. This will minimize the total generation cost for the system with the voltage level maintained at the safe operating limits. There by, fulfilling the main objective.

Economic dispatch is defined as the process of allocating generation levels to the generating units in the mix so that the system load is fully supplied in the most economic way. The method of economic dispatch for generating units at different loads must have total fuel cost at the minimum point. There are many conventional methods that are in use to solve economic dispatch problem such as Lagrange multiplier method, Lambda iteration method and Newton method. In the conventional methods, it is difficult to solve the optimal economic problem if the load is changed. It needs to compute the economic dispatch each time which uses a long time in each of computation loops.

It is a computational process where the total required generation is distributed among the generation units in operation, by minimizing the selected cost criterion, and subjects it to load and operational constraints as well.

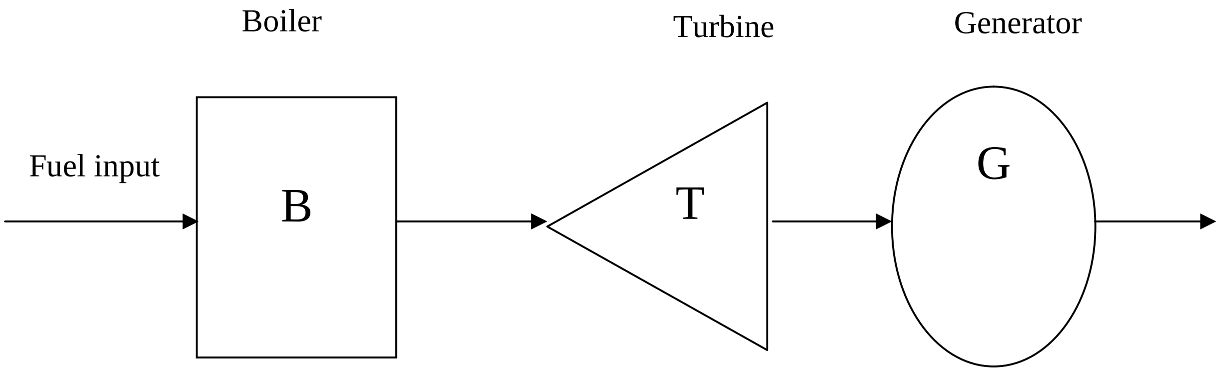
2.2 DYNAMIC ECONOMIC DISPATCH

The DED is a dynamic problem due to the dynamic nature of power system and the large variation of load demand [37, 38]. This absolute problem is normally solved by discretisation of the entire dispatch period into a number of small time intervals over which the load is assumed to be constant and the system is considered to be in temporal steady-state. To achieve the overall cost reduction in operating a power system, the individual static interval should be dispatched economically through static economic dispatch (SED) and subject to static constraints at that time while the additional limits put on by a stream of time dependent dynamic constraints [41, 42].

Traditional economic dispatch problem, attempts to minimize the cost of supplying energy subject to constraints on static behaviour of the generating units. It is assumed that the amount of power to be supplied by a given set of units is constant for a given interval of time. However, to avoid shortening of the life of their equipment, plant operators, try to keep thermal gradients inside the turbine within safe limits. This mechanical constraint is usually translated into a limit on the rate of increase of the electrical output. Such ramp rate constraints distinguish the DED problem from traditional static economic dispatch. The DED may be considered as the latest developments in economic dispatch [37, 38]. The DED serves to schedule the generator outputs with the predicted load demands over a certain period of time so as to operate an electric power system most economically. The DED, an extension of conventional economic dispatch problem, refers to the problem of determining minimum system cost of dispatch of generators, taking into consideration the constraints imposed on system operation by the generator ramping rate limitations [46].

2.3 GENERATOR OPERATING COST

The total cost of operation includes the fuel cost, cost of labour, supplies and maintenance. Generally, costs of labour, supplies and maintenance are fixed percentages of incoming fuel costs. The power output of fossil plants is increased sequentially by opening a set of valves to its steam turbine at the inlet. The throttling losses are large when a valve is just opened and small when it is fully opened.



(Figure-2.1 Simple model of a fossil plant)

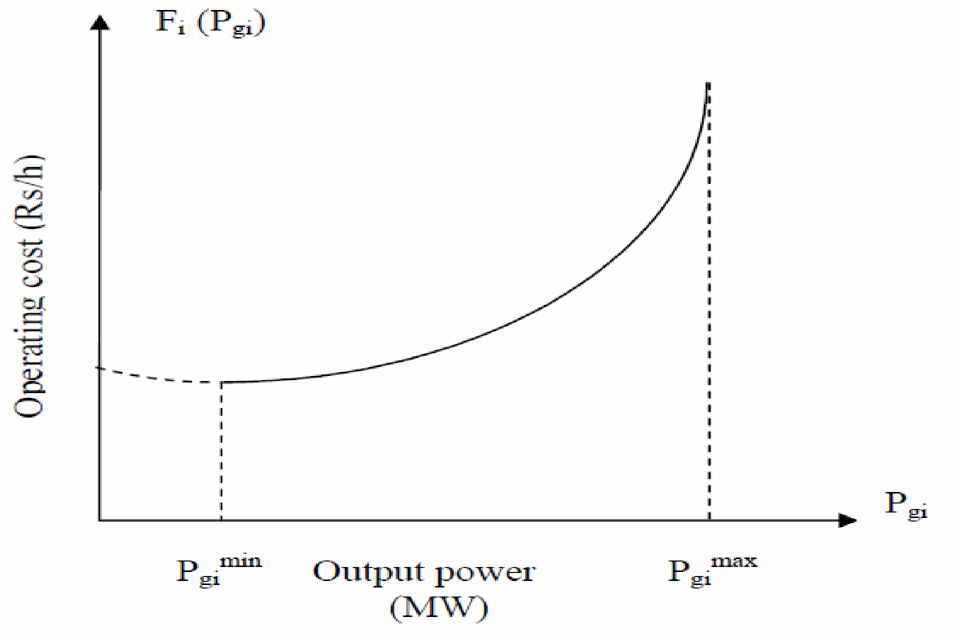
Fig-2.1 shows the simple model of a fossil plant dispatching purposes. The cost is usually approximated by one or more quadratic segments.

So, the fuel cost curve in the active power generation, takes up a quadratic form, given as

$$F(P_{gi})= a_iP^2_{gi}+ b_iP_{gi}+ c_i Rs/hr \qquad (2.1)$$

The fuel cost curve may have a number of discontinuities. The discontinuities occur when the output power is extended by using additional boilers, steam condensers, or other equipment. They may also appear if the cost represents the operation of an entire power station, and hence cost has discontinuities on paralleling of generators.

Within the continuity range the incremental fuel cost may be expressed by a number of short line segments or piece-wise linearization.



(Figure-2.2 Operating costs of a fossil fired generator

The Pgi^{min} is the minimum loading limit below which, operating the unit proves to be uneconomical (or may be technically infeasible) and Pgi^{max} is the maximum output limit.

2.4 THE ECONOMIC DISPATCH PROBLEM

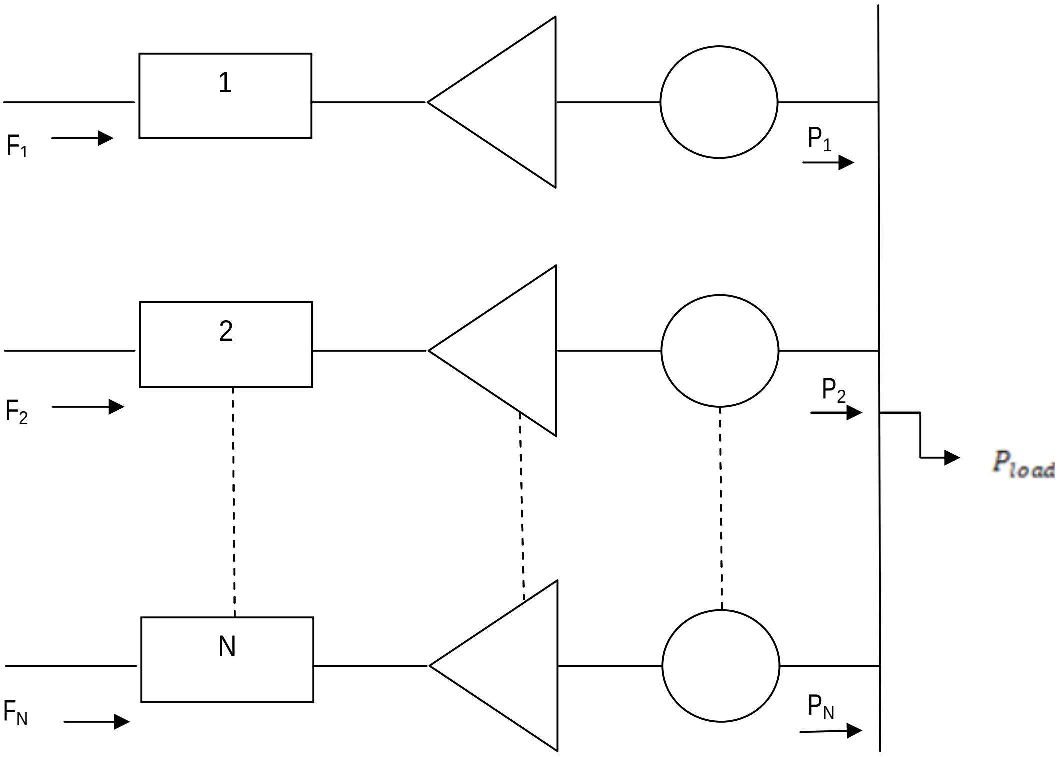
This system consists of N thermal-generating units connected to a single bus-bar serving a received electrical load P_{load} .The input to each unit, shown as F_i represents the cost rate of the unit. The output of each unit, P_i, is the electrical power generated by that particular unit. The total cost rate of this system is, of course, the sum of the costs of each of the individual units. The essential constraint on the operation of this system is that the sum of the output powers must equal the load demand [26].

Figure-2.3 shows the configuration that will be studied in this section. Mathematically speaking, the problem may be stated very concisely. That is, an objective function, F_T, is equal to the total cost for supplying the indicated load. The problem is to minimize F_T subject to the constraint that the sum of the powers generated must equal the received load. That is,

$$F_T = F_1 + F_2 + F_3 + \dots\dots\dots + F_N \tag{2.2}$$

$$F_T = \sum_{i=1}^{N} F_i(P_i) \tag{2.3}$$

$$\phi = 0 = P_{Load} - \sum_{i=1}^{N} P_i \tag{2.4}$$



(Figure-2.3 N thermal units committed to serve a load of P_{load})

This is a constrained optimization problem that may be attacked formally using advanced calculus methods that involve the Lagrange function.

This is known as the Lagrange function and is shown.

$$\ell = F_T + \lambda\varphi \tag{2.5}$$

In order to establish the necessary conditions for an extreme value of the objective function, add the constraint function to the objective function after the constraint function has been multiplied by an undetermined multiplier.

The necessary conditions for an extreme value of the objective function result when we take the first derivative of the Lagrange function with respect to each of the independent variables and set the derivatives equal to zero. In this case, there is N+ 1 variable, the N values of power output, P_i, plus the undetermined Lagrange multiplier, λ. The derivative of the Lagrange function with respect to the undetermined multiplier merely gives back the constraint equation. On the other hand, the N equations that result when we take the partial derivative of the Lagrange function with respect to the power output values one at a time give the set of equations shown as

$$\frac{\partial l}{\partial P_i} = \frac{dF_i}{dP_i} - \lambda = 0 \qquad (2.6)$$

$$0 = \frac{dF_i}{dP_i} - \lambda \qquad (2.7)$$

That is, the necessary condition for the existence of a minimum cost operating condition for the thermal power system is that the incremental cost rates of all the units be equal to some undetermined value, λ. Of course, to this necessary condition we must add the constraint equation that the sum of the power outputs must be equal to the power demanded by the load. In addition, there are two inequalities that must be satisfied for each of the units. That is, the power output of each unit must be greater than or equal to the minimum power permitted and must also be less than or equal to the maximum power permitted on that particular unit. These conditions and inequalities may be summarized as shown in the set of equations making up.

$$\frac{dF_i}{dP_i} = \lambda \qquad \text{N equations} \qquad (2.8)$$

$$P_{i,\min} \le P_i \le P_{i,\max} \qquad \text{2N inequalities} \qquad (2.9)$$

$$\sum_{i=1}^{N} P_i = P_{Load} \qquad \text{1 constraint} \qquad (2.10)$$

When we recognize the inequality constraints, then the necessary conditions may be expanded slightly as shown in the set of equations making up eq. (2.11)

$$\begin{aligned} \frac{dF_i}{dP_i} &= \lambda \text{ for, } P_i\text{, min} < P_i < P_i\text{,max} \\ \frac{dF_i}{dP_i} &\le \lambda \text{ for, } P_i = P_i\text{,max} \qquad (2.11) \\ \frac{dF_i}{dP_i} &\ge \lambda \text{ for, } P_i = P_i\text{,min} \end{aligned}$$

2.5 THERMAL SYSTEM DISPATCHING WITH NETWORK LOSSES CONSIDERED

The economic dispatching problem associated with this particular configuration is slightly more complicated to set up than the previous case. This is because the constraint equation is now one that must include the network losses. Figure-2.4 shows symbolically an all-thermal power generation system connected to an equivalent load bus through a transmission network. The objective function, F_T, is the same as that defined. However, the constraint equation previously shown must now be expanded to the one shown.

$$P_{LOAD} - P_{LOSS} - \sum_{i=0}^{N} P_i = \phi = 0 \tag{2.12}$$

The same procedure is followed in the formal sense to establish the necessary conditions for a minimum-cost operating solution. In taking the derivative of the Lagrange function with respect to each of the individual power outputs P_i it must be recognized that the loss in the transmission network, P_{loss} is a function of the network impedances and the currents flowing in the network. For our purposes, the currents will be considered only as a function of the independent variables P_i and the load P_{load} Taking the derivative of the Lagrange function with respect to any one of the *N* values of P_i results. There are *N* equations of this type to be satisfied along with the constraint equation**.**

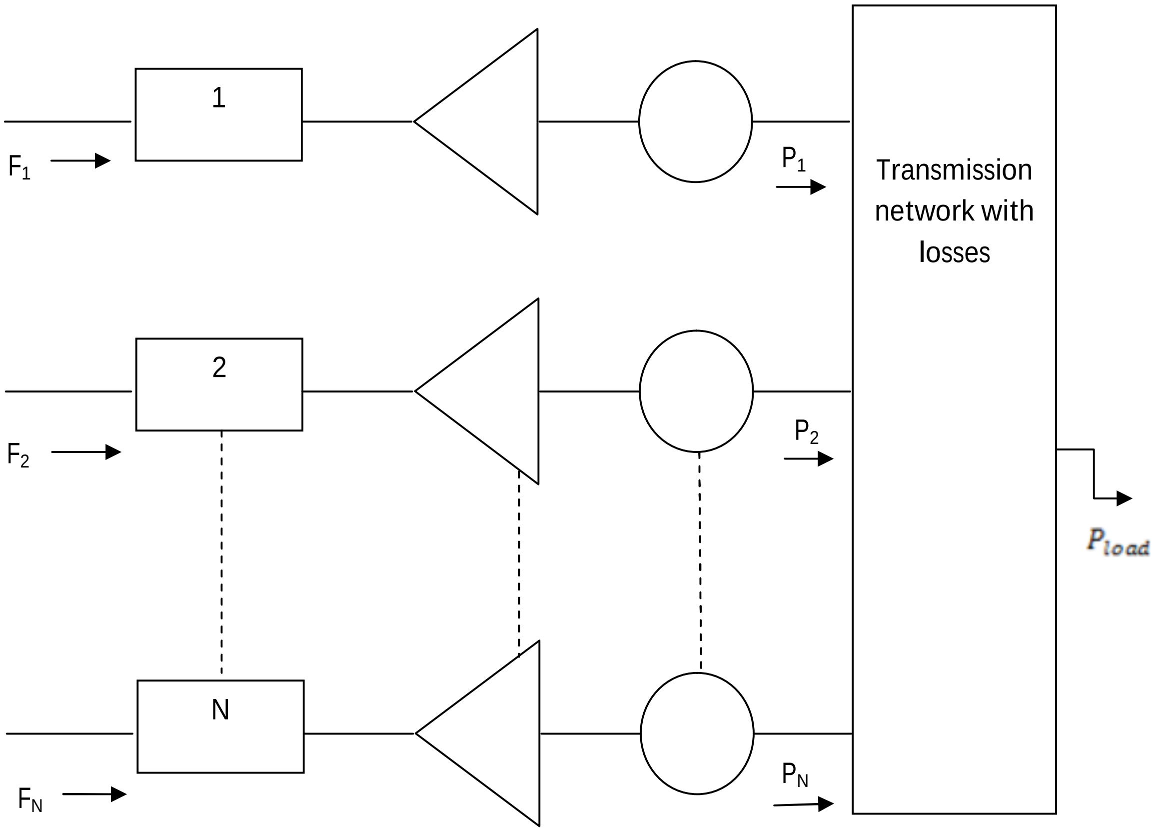
$$l = F_t + \lambda\phi \tag{2.13}$$

$$\frac{dF_i}{dP_i} + \lambda \frac{dP_{Loss}}{dP_i} = \lambda \tag{2.14}$$

$$P_{Load} + P_{Loss} - \sum_{i=0}^{N} P_i = 0 \tag{2.15}$$

$$\frac{\partial l}{\partial P_i} = \frac{\partial F_i}{\partial P_i} - \left(1 - \frac{\partial P_{Loss}}{\partial P_i}\right) = 0 \tag{2.16}$$

$$P_{Load} + P_{Loss} - \sum_{i=0}^{N} P_i = 0 \tag{2.17}$$



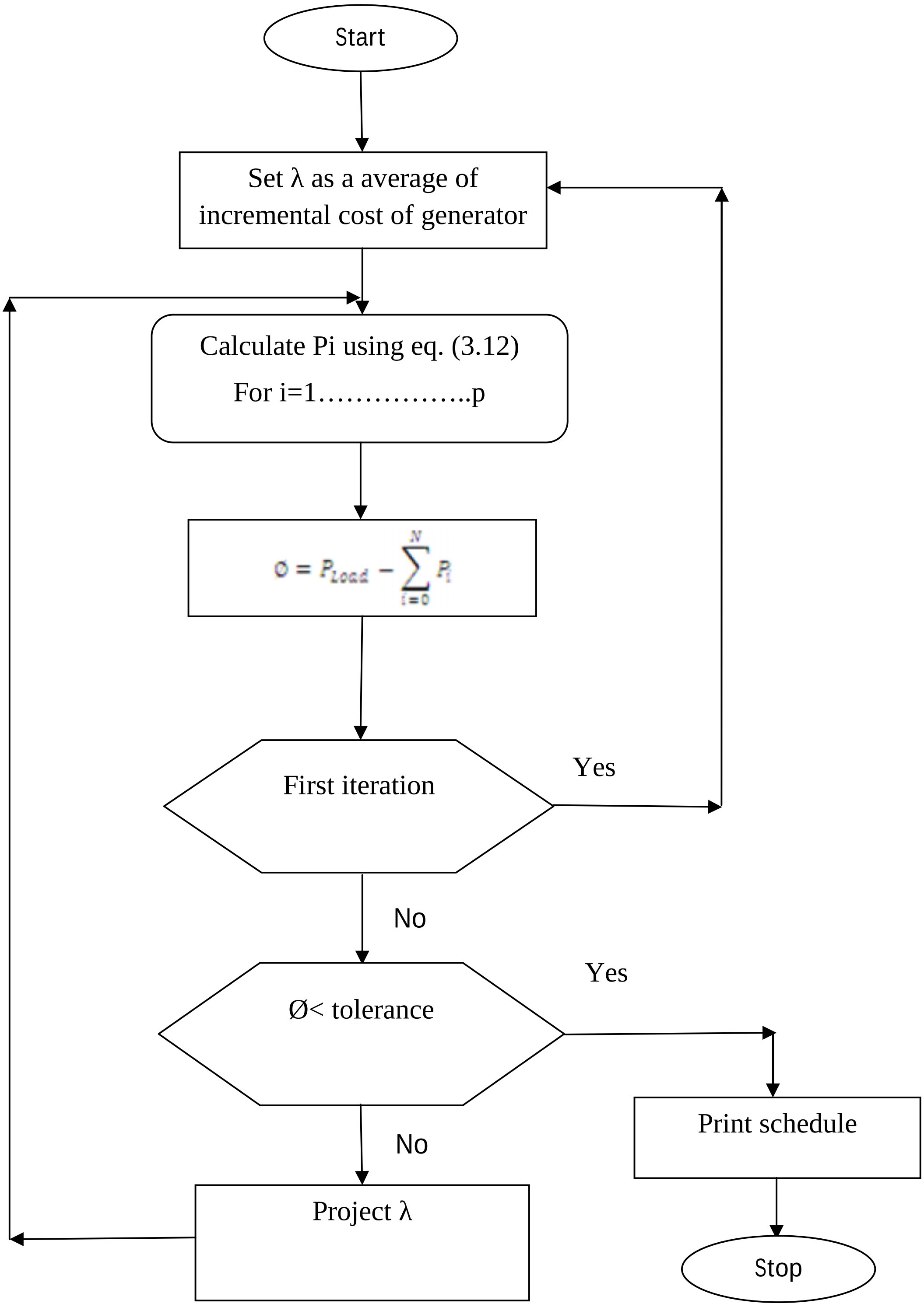
(Figure-2.4 N thermal units serving load through transmission network)

It is much more difficult to solve this set of equations than the previous set with no losses since this second set involves the computation of the network loss in order to establish the validity of the solution in satisfying the constraint equation. There have been two general approaches to the solution of this problem.

The first step of a mathematical expression for the losses in the network solely as a function of the power output of each of the units. The other basic approach to the solution of this problem is to incorporate the power flow equations as essential constraints in the formal establishment of the optimization problem. This general approach is known as the optimal power flow.

2.6 THE LAMBDA-ITERATION METHOD

Figure-2.5 is a flow chart of the lambda-iteration method of solution for the all-thermal, dispatching problem-neglecting losses. We can approach the solution to this problem by considering a graphical technique for solving the problem and then extending this into the area of computer algorithms.



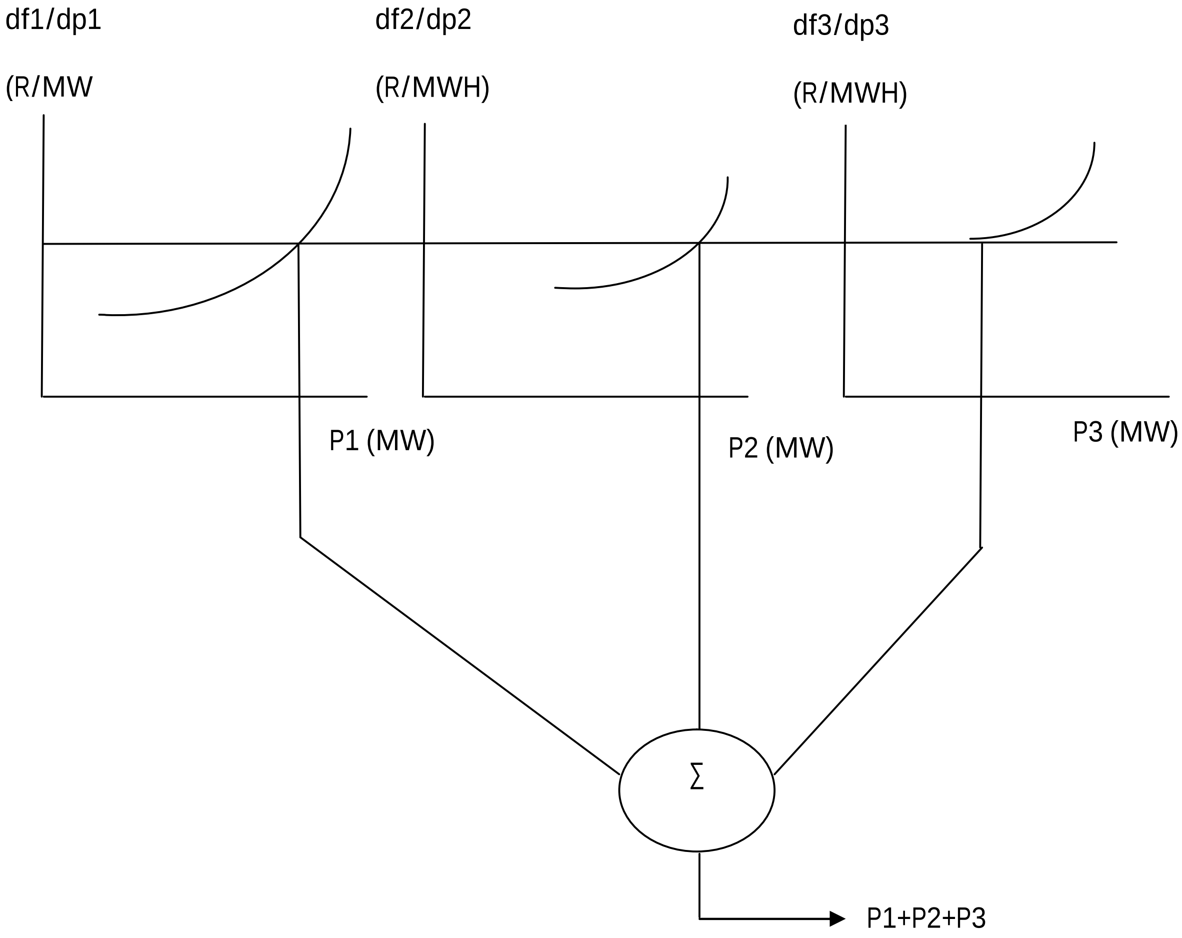
(Figure-2.5 Flow chart of economic dispatch by the lamda-iteration method)

Suppose we have a three-machine system and wish to find the optimum economic operating point. One approach would be to plot the incremental cost characteristics for each of these three units on the same graph, such as sketched in

Figure-2.6. In order to establish the operating points of each of these three units such that we have minimum cost and at the same time satisfy the specified demand, we could use this sketch and a ruler to find the solution. That is, we could assume an incremental cost rate **λ** and find the power outputs of each of the three units for this value of incremental cost.

By keeping track of the total demand versus the incremental cost, we can rapidly find the desired operating point. If we wished, we could manufacture a whole series of tables that would show the total power supplied for different incremental cost levels and combinations of units. This same procedure can be adopted for a computer implementation as shown in Figure-2.6.

That is, we will now establish a set of logical rules that would enable us to accomplish the same objective as we have just done with ruler and graph paper. The actual details of how the power output is established as a function of the incremental cost rate are of very little importance.



(Figure-2.6 Graphical solution to economic dispatch)

This procedure is an iterative type of computation, and we must establish stopping rules. Two general forms of stopping rules seem appropriate for this application. The first is shown in Figure-2.5 and is essentially a rule based on finding the proper operating point within a specified tolerance. The other, not shown in Figure-2.5, involves counting the number of times through the iterative loop and stopping when a maximum number is exceeded.

The lambda-iteration procedure converges very rapidly for this particular type of optimization problem. The actual computational procedure is slightly more complex than that indicated in Figure-2.5, since it is necessary to observe the operating limits on each of the units during the course of the computation.

2.7 GRADIENT METHODS OF ECONOMIC DISPATCH

Lambda search technique always requires that one be able to find the power output of a generator, given an incremental cost for that generator. In the case of a quadratic function for the cost function, or in the case where the incremental cost function is represented by a piecewise linear function, this is possible. However, it is often the case that the cost function is much more complex, such as the one below

$$\mathrm{F}(\mathrm{P}) = \mathrm{A} + \mathrm{BP} + \mathrm{CP}^2 + \mathrm{D}\exp\left[\frac{(\mathrm{P}-\mathrm{E})}{\mathrm{F}}\right] \tag{2.18}$$

In this case, we shall propose that a more basic method of solution for the optimum be found.

2.7.1 GRADIENT SEARCH

This method works on the principle that the minimum of a function, f(x), can be found by a series of steps that always take us in a downward direction. From any starting point, x^o, we may find the direction of “steepest descent” by noting that the gradient off, i.e.

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial X_1} \\ \cdot \\ \cdot \\ \cdot \\ \frac{\partial f}{\partial X_n} \end{bmatrix} \tag{2.19}$$

Always points in the direction of maximum ascent. Therefore, if we want to move in the direction of maximum descent, we negate the gradient. Then we should go from x^o to x^1 using

$$X^1 = X^0 - (\nabla f)\alpha \tag{2.20}$$

Where α is a scalar to allow us to guarantee that the process converges.

2.7.2 ECONOMIC DISPATCH BY GRADIENT SEARCH

The object is to drive the function to its minimum. However, we have to be concerned with the constraint function.

$$f = \sum_{i=1}^{N} F_i(P_i) \tag{2.21}$$

To solve the economic dispatch problem which involves minimizing the objective function and keeping the equality constraint, we must apply the gradient technique directly to the Lagrange function itself.

$$\phi = P_{Load} - \sum_{i=0}^{N} P_i \tag{2.22}$$

The Lagrange function is

$$\ell = \sum_{i=1}^{N} F_i(P_i) + \lambda(P_{load} - \sum_{i=1}^{N} P_i) \tag{2.23}$$

and the gradient of this function is

$$\nabla \ell = \begin{bmatrix} \frac{\partial \ell}{\partial P_1} \\ \frac{\partial \ell}{\partial P_2} \\ \frac{\partial \ell}{\partial P_3} \\ \frac{\partial \ell}{\partial \lambda} \end{bmatrix} = \begin{bmatrix} \frac{d}{dP_1} F_1(P_1) - \lambda \\ \frac{d}{dP_2} F_2(P_2) - \lambda \\ \frac{d}{dP_3} F_3(P_3) - \lambda \\ P_{load} - \sum_{i=1}^{N} P_i \end{bmatrix} \tag{2.24}$$

The economic dispatch algorithm requires a starting, λ value and starting values for P_l,P_2, and P_3**.** The gradient for £ is calculated as above and the new values of λ, P_l,P_2, and P_3 etc., are found from

$$X^1 = X^0 - (\nabla \ell)\alpha \tag{2.25}$$

Where the vector x is

$$X = \begin{bmatrix} P1 \\ P2 \\ P3 \\ . \\ . \\ . \\ \lambda \end{bmatrix} \tag{2.26}$$

The problem with this formulation is the lack of a guarantee that the new points generated each step will lie on the surface Φ. We shall see that this can be overcome by a simple variation of the gradient method.

2.8 DISPATCHING THE POWER SYSTEM TODAY

a) Monitor load, generation and interchange (imports/exports) to ensure balance of supply and load.

  - Monitor and maintain system frequency during dispatch according to NERC standards, using Automatic Generation Control (AGC) to change generation dispatch as needed.
  - Monitor hourly dispatch schedules to ensure that dispatch for the next hour will be in balance

b) Monitor flows on transmission system

  - Keep transmission flows within reliability limits
  - Keep voltage levels within reliability ranges

  Take corrective action, when needed, by.

  1. Limiting new power flow schedules
  2. Curtailing existing power flow schedules
  3. Changing the dispatch
  4. Shedding load

c) This monitoring is typically performed by the transmission operator

2.9 PLANNING FOR TOMORROW’S DISPATCH

Scheduling generating units for each hour of the next day’s dispatch

a. Based on forecast load for the next day
b. Select generating units to be running and available for dispatch the next day (operating day)
c. Recognize each generating unit’s operating limit, including its
    - Ramp rate (how quickly the generator’s output can be changed)
    - Maximum and minimum generation levels
    - Minimum amount of time the generator must run
    - Minimum amount of time the generator must stay off once turned off

Recognize generating unit characteristics, including:

1. Cost of generating, which depends on
    - Its efficiency (heat rate)
    - Its variable operating costs (fuel and non-fuel)
2. Variable cost of environmental compliance
3. Start-up costs

Next day scheduling is typically performed by a generation group or an independent market operator.

- Reliability Assessment
- Analyse forecasted load and transmission conditions in the area to ensure that scheduled generation dispatch can meet load reliably.
- If the scheduled dispatch is not feasible within the limits of the transmission system, revise it.
- This reliability assessment is typically performed by a transmission operations group.

2.10 RESOURCE CONSIDERATIONS AFFECTING ECONOMIC DISPATCH

A variety of physical, environmental, and regulatory considerations affect how resources can be used and combined in the economic dispatch process, and a combination of attributes determines how each generation resource is identified and treated in the process. Depending on the dispatch regime, those factors may include.

- Real and reactive energy-production capacity.
- Variable operations and maintenance costs.
- Whether a unit is on a cost-based, reliability-must-run (RMR) contract or its production cost curve is based on fuel costs and efficiency rates (or, in centralized wholesale markets, bids for production at differing levels on its output curve).
- A unit’s prior commitments to make off-system sales.
- A unit’s mechanical or economical upper and lower production levels.
- Minimum sustained production levels (to keep the unit available for the next hour or next day).
- Emissions limit and cost of emission allowances (because units that use up their emissions allowances prematurely may not be available to operate during peak periods).
- For a hydro, wind, or other intermittent units, a forecast of expected unit production levels at different points in the dispatch period.
- Contracts or other requirements that assign a unit must-run or must-take status so that is not fully dispatch able.
- Start-up cost
- A unit’s ability and contractual requirement to deliver ancillary services, such as reactive power or quick-start capability.
- Unit ramp rates within the range of production levels (e.g., the time it takes to move from one production level to another while respecting the turbine’s safe thermal gradients).

Some of these factors, such as minimum production levels, will dictate whether a unit will be in the base level or the competitive region of the economic dispatch stack. These requirements are treated as “constraints” in the cost-minimization procedures used by the utilities for economic dispatch. These concerns can be reflected in the dispatch process, whether as formal limitations on the selection of resources or as qualifiers on the utilization of specific resources.

CHAPTER # 3

PARTICLE SWARM OPTIMIZATION (PSO)

3.1 INTRODUCTION

Particle Swarm Optimization (PSO) is a population-based continuous optimization technique proposed by Kennedy and Eberhart (1995). Like ant colony optimization algorithms (Dorigo et al. 1996) or genetic algorithms (Holland 1992), PSO is biologically inspired. In this case, the algorithm is inspired by the social behaviour of animals living in groups (Reynolds 1987; Wilson 1975) [16]. The algorithm simulates a simplified social milieu in a swarm of potential solutions (called “particles”), which means that a single particle bases its search not only on its own experience but also on the information given by its neighbours in the swarm. This paradigm leads to successful results and contributes to the popularity of PSO [13], [15].

The performance of a given algorithm is strongly dependent on the values assigned to its parameter set (Shi and Eberhart 1998). Hence, the parameters of the algorithm must be carefully tuned in order to achieve an optimal performance. Evidently, the time spent to find the optimal parameter set increases with the number of parameters. PSO requires tuning of a set of parameters. For example, the size of the swarm and the inertia weight are two of the parameters of the algorithm. However, there are applications where the user cannot afford to spend a lot of time in determining an optimal set of parameters on a trial and error basis. In case the objective function values are being obtained by a slow experimental process, conducting repeated tests with different parameter sets becomes impractical [11-13].

Particle swarm optimization can be used to solve many of the same kinds of problems as genetic algorithms. This optimization technique does not suffer, however, from some of GA’s difficulties; interaction in the group enhances rather than detracts from progress toward the solution. Further, a particle swarm system has memory, which the genetic algorithm does not have. Change in genetic populations results in destruction of previous knowledge of the problem, except when elitism is employed, in which case usually one or a small number of individuals retain their “identities.” In particle swarm optimization, individuals who fly past optima are tugged to return toward them; knowledge of good solutions is retained by all particles. Particle swarm optimization has also been demonstrated to perform well on genetic algorithm test functions, and it appears to be a promising approach for robot task learning.

3.2 BASIC PARTICLE SWARM OPTIMIZATION

Particle swarm optimization has roots in two main component methodologies. Perhaps more obvious are its ties to artificial life (A-life) in general, and to bird flocking, fish schooling, and swarming theory in particular. It is also related, however, to evolutionary computation, and has ties to both genetic algorithms and evolution strategies. Particle swarm optimization comprises a very simple concept, and paradigms are implemented in a few lines of computer code. It requires only primitive mathematical operators, and is computationally inexpensive in terms of both memory requirements and speed. Early testing has found the implementation to be effective with several kinds of problems. Particle swarm optimization has also been demonstrated to perform well on genetic algorithm test functions, and it appears to be a promising approach for robot task learning.

3.2.1 BACKGROUND OF PARTICLE SWARM OPTIMIZATION

Swarm behaviour can be modelled with a few simple rules. Schools of fish and swarms of birds can be modelled with such simple models. Namely, even if the behaviour rules of each individual (agent) are simple, the behaviour of the swarm can be complicated. Reynolds utilized the following three vectors as simple rules in the researches on void [16].

1. Step away from the nearest agent
2. Go toward the destination
3. Go to the centre of the swarm

The behaviour of each agent inside the swarm can be modelled with simple vectors. The research results are one of the basic backgrounds of PSO. Boyd and Richerson examined the decision process of humans and developed the concept of individual learning and cultural transmission. According to their examination, people utilize two important kinds of information in decision process. The first one is their own experience; that is, they have tried the choices and know which state has been better so far, and they know how good it was. The second one is other people's experiences; that is, they have knowledge of how the other agents around them have performed. Namely, they know which choices their neighbours have found most positive so far and how positive the best pattern of choices was. Each agent decides its decision using its own experiences and the experiences of others. The research results are also one of the basic background elements of PSO.

3.2.2 BASIC PSO

According to the above background of PSO, Kennedy and Eberhart developed PSO through simulation of bird flocking in a two-dimensional space. The position of each agent is represented by its x, y axis position and also its velocity is expressed by v_x (the velocity of x axis) and v_y (the velocity of y axis). Medication of the agent position is realized by the position and velocity information. Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests. This information is an analogy of knowledge of how the other agents around them have performed. Each agent tries to modify its position using the following information

- The current positions (x, y),
- The current velocities (v_x, v_y),
- The distance between the current position and pbest
- The distance between the current position and gbest

This modification can be represented by the concept of velocity (modified value for the current positions). Velocity of each agent can be modified by the following equation

$$V_i^{(t+1)} = wV_i^t + C_1R_1\left(X_{lbesti} - X_i^t\right) + C_2R_2\left(X_{gbest} - X_i^t\right) \qquad (3.1)$$

where V_i^t is velocity of agent i at iteration t, w is weighting function, C_1, C_2 is accelerating constant and choose value of C_1, C_2 is 2, R_1, R_2 is random number between 0 and 1, X_i^t is current position of agent i at iteration t, lbesti is lbest of agent i, and gbest is gbest of the group.

Namely, velocity of an agent can be changed using three vectors such like void. The velocity is usually limited to a certain maximum value. PSO using (3.1) is called the gbest model.

3.3 PARAMETER SELECTION IN PARTICLE SWARM OPTIMIZATION

To ensure convergence of PSO adjustments of various parameters need to be carefully adjusted in order to achieve better performance of the algorithm. In the subsequent section, the detailed implementation strategies of the PSO are described

3.3.1 ACCELERATION CONSTANT

Here in this thesis we used C_1 and C_2 as a constant. The constants C_1 and C_2 represent the weighting factor of the acceleration terms that pull each particle toward the pbest and gbest positions.

3.3.2 VELOCITY UPDATING

$$V_i^{(t+1)} = V_i^t + C_1R_1(X_{lbesti} - X_i^t) + C_2R_2(X_{gbest} - X_i^t) \qquad (3.2)$$

Where i = 1………..n ,   d = 1………..m

n - Population size

m - Number of unit dimension

C_1, C2 - acceleration constant

R_1, R2 - uniform random value in large (0-1)

V_i - velocity of particle ‘ i ’ at iteration ‘t ’

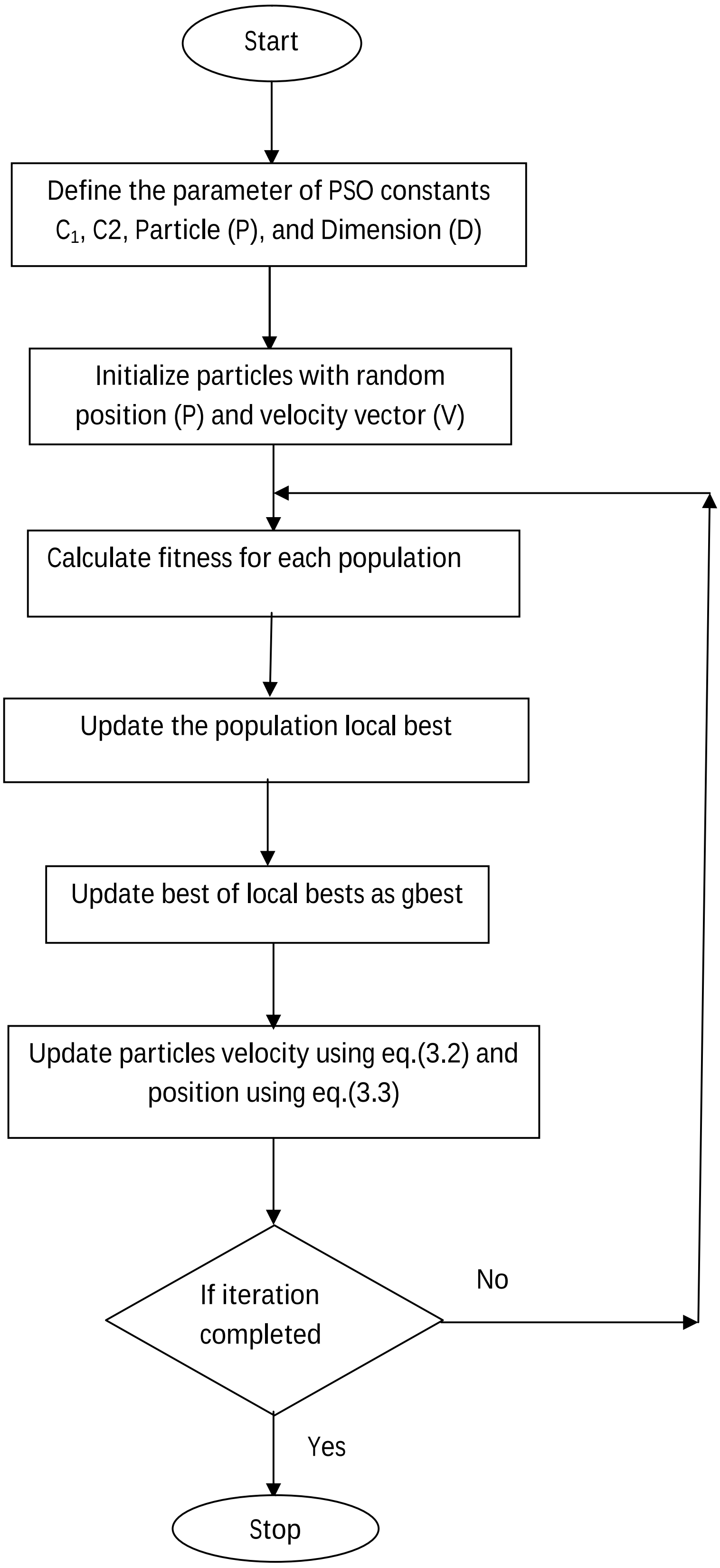
V_i^t - (modified) velocity of particle ‘i’ at iteration‘t ’

3.3.3 POSITION MODIFICATIONS

$$X_i^{t+1} = X_i^t + V_i^{(t+1)} \qquad (3.3)$$

X_i^{t+1} – Modified position of particle 'i ' at iteration (t +1)

3.4 FLOW CHART OF BASIC PSO



(Figure-3.1 Flow chart of basic pso)

3.5 ALGORITHEM OF PSO

The step-by-step algorithm for the proposed method is explained as follows

STEP 1- Specify the maximum and minimum limits of generation power of each generating unit, maximum number of iterations to be performed and fuel cost co-efficient of each unit.

STEP 2 - Initialize randomly the individuals of the population of all units according to the limit of each unit.

STEP 3- Evaluate the fitness function of each particle.

STEP 4- For each individual particle; compare the particle's fitness value with lbest. If the current value is better then the lbest, then set this value as the current particle's position as lbest.

STEP 5- Check the velocity V of each particle according to

If $$V_i^{(t+1)} > V^{max}, \text{ then } V_i^{(t+1)} = V^{max} \tag{3.4}$$

$$V_i^{(t+1)} > V^{min}, \text{ then } V_i^{(t+1)} = V^{min} \tag{3.5}$$

STEP 6- Modify the member position of each individual X_i according to equation (3.3).

STEP 7- Repeat step (3-6) until a stopping criterion is met (e.g., maximum number of iteration or a sufficiently good fitness value).

CHAPTER # 4

DYNAMIC ECONOMIC DISPATCH USING PARTICLE SWARM OPTIMIZATION (PSO)

4.1 INTRODUCTION

Power system economic load dispatch is the process of allocating generation among the available generating units subject to load and other operational constraints, such that, the cost of operation is minimum. It is essential for real-time control of power system operation [11]. The output of a static procedure is a sequence of separate optimal points, which do not take into account the existing dynamic connections among the system state variables during the optimization interval [37, 38].

The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods. Although the PSO seems to be sensitive to the tuning of some weights or parameters, many researchers are still in progress for proving its potential in solving complex power system problems. Compared to other evolutionary computation techniques, PSO can solve the problems quickly with high quality solutions and stable convergence characteristics, whereas it is easily implemented. However, PSO can sometimes suffer from the lack of the diversity amongst the particles, which can lead to a stagnation stage [8]. Therefore, although PSO has been a subject of an extensive research, there is a number of issues that need to be addressed in order to exploit the full potential of PSO in solving complex power system problems [9].

Recent research endeavours have, therefore, been directed towards application of other efficient global search techniques like PSO. The PSO is a relatively new family of algorithms that may be used to find optimal or near optimal solutions to numerical and qualitative problems. It is easy to implement in most programming languages and has been proved to be quite effective and reasonably quick when applied to a diverse set of optimization problems [40-43].

The PSO shares many similarities with evolutionary computation techniques, such as, genetic algorithms (GA). The system is initialized with a population of random solutions and then 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 with randomized velocity through the problem hyperspace. Compared to GA, the advantages of PSO are in the facts that it is easy to implement and there are only a few parameters to adjust.

Particle swarm optimization is a potential solution, accelerating towards “better” solutions. Other evolutionary computation schemes operate directly on potential solutions. It appears that the current version of the paradigm allocates trials which are near to optimal solutions. The algorithm is written in a very few lines of code, and requires only specification of the problem and a few parameters in order to solve it. This algorithm belongs ideologically to that philosophical school that allows wisdom to emerge rather than trying to impose it. Once again nature has provided us with a technique for processing information that is at once elegant and versatile.

4.2 PSO IMPLEMENTATION TO DYNAMIC ECONOMIC DISPATCH

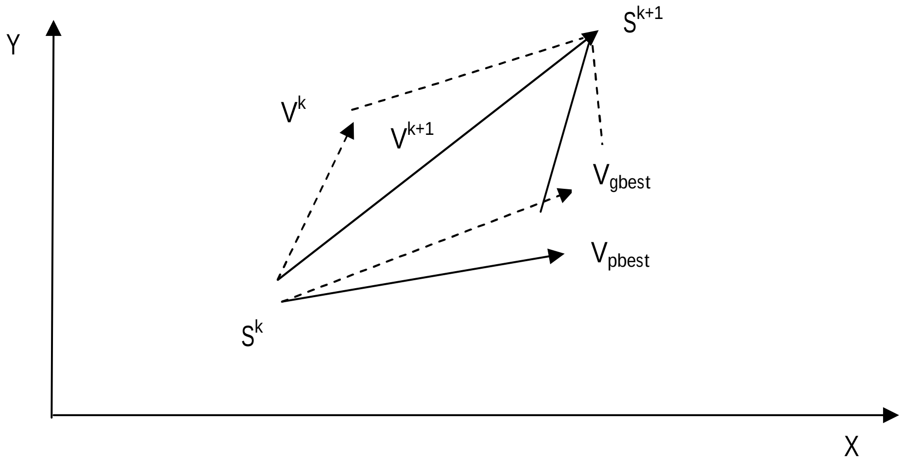
The practical ED problems with equality and inequality constraints with valve-point and multi fuel effects are represented as a non smooth optimization problem, and this makes the problem of finding the global optimum difficult.

To solve this problem, many salient methods have been proposed such as a mathematical approach dynamic programming, evolutionary programming tabu search neural network approaches and genetic algorithm In this section, an alternative approach is proposed to the non smooth ED problem using a PSO which focuses on the treatment of the equality and inequality constraints when modifying each individual’s search.

The economic dispatch (ED) optimization problem is one of the fundamental issues in power systems to obtain optimal benefits with the stability, reliability and security. Various optimization methods and techniques have been researched. In the conventional methods such as the lambda-iteration method, the base point and participation factors, and the gradient methods, an essential assumption is that the incremental cost curves of the units are monotonically increasing piece wise linear functions, but the practical systems are nonlinear [40-43]. Hence, global optimization techniques, such as genetic algorithm, simulated annealing (SA), and particle swarm optimization (PSO) have been studies in the past decade and have been successfully used to solve the ED. Most of the existing PSO approaches were based on the basic particle swarm optimization (BPSO).

4.2.1 GENERATION OF INITIAL CONDITION

Initial searching points and velocities of each agent are usually generated randomly with in the allowable range. The current searching point is set to pbest for each agent. The best- evaluated value of pbest is set to gbest and the agent number with the best value is stored.



(Figure-4.1 Concept of modification of searching point by PSO)

4.2.2 EVALUATION OF SEARCHING POINT

The value of the objective function is calculated for each agent. If the value is better than the current pbest of the agent, the pbest value is replaced by the current value. If the best value of pbest is better than the current gbest, gbest is replaced by the best value and the agent number with the best value is stored.

4.2.3 DYNAMIC ECONOMIC DISPATCH ALGORITHM

An algorithm based on particle swarm optimization for solving the dynamic economic dispatch is described here.

$$P_k = [(P_{11}, P_{21}, \dots\dots, P_{i1} \dots\dots, P_{N1}), \dots\dots, (P_{1m}, P_{2m}, \dots\dots, P_{im} \dots\dots, P_{Nm}), \dots]$$

The trial vector designating kth particle of the population and k=1, 2, 3,...Np. The elements of P_k are real power outputs of N generating units over m time sub-intervals.

The objective is to minimize F and the algorithm can be described as follows.

Step 1 -Input the system data consisting of fuel cost curve coefficients of generators, power generation limits.

Step 2 -Initialize the particles of the population according to the limits of each unit including dimensions.

Step 3 - Calculate and compare the cost value Fit (P_k) for each individual P_k in the population.

Step 4 – Particle correspondence the lowest fitness will be pbest. If the new cost value for P_k is less than that obtained with pbestk, then replace the coordinates of pbestk with the present coordinates of P_k.

Step 5 - Compare the fitness values of pbestk of all particles to determine the best particle. Store the coordinates of the best particle as gbest.

Step 6 - Modify the member velocity of each particle according to equation (4.1).

$$V_i^{(t+1)} = V_i^t + C_1R_1(X_{lbesti} - X_i^t) + C_2R_2(X_{gbest} - X_i^t) \qquad (4.1)$$

Step 7 - Modify the member position of each particle according to equation (4.2).

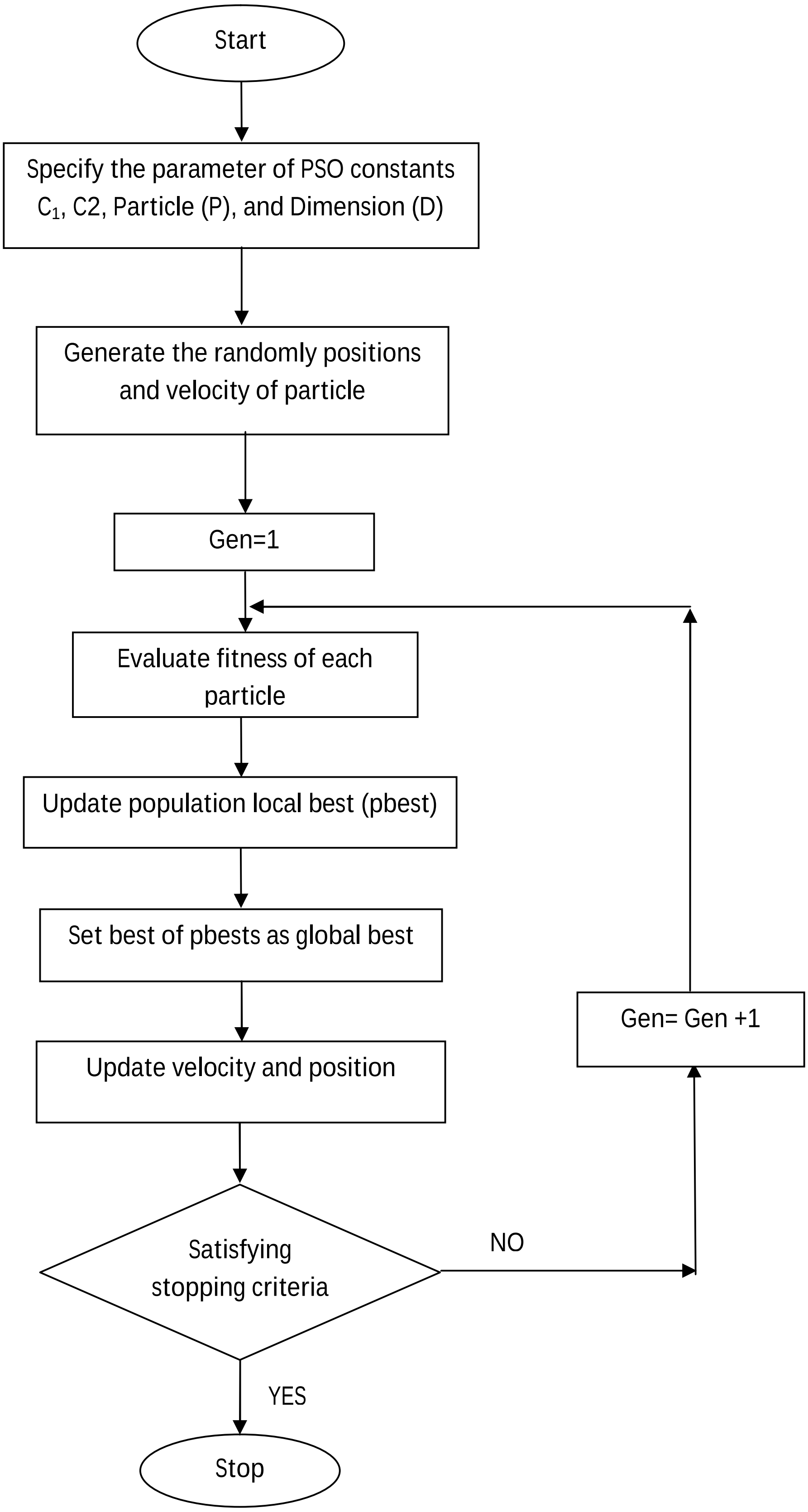
$$X_i^{t+1} = X_i^t + V_i^{(t+1)} \qquad (4.2)$$

Step 8 - If the number of iterations reaches the maximum, then go to Step 9. Otherwise, go to Step 3.

Step 9 - The particle that generates the latest gbest is the solution of the problem.

Step 10 – Stop

4.2.4 PSO BASED DYNAMIC ECONOMIC DISPATCH FLOW CHART



(Figure-4.2 Flow chart of PSO based dynamic economic dispatch)

4.3 DYNAMIC ECONOMIC DISPATCH PROBLEM FORMULATIONS

DED (dynamic economic dispatch) is to schedule the outputs economically over a certain period of time under various system and operational constraints.

4.3.1 OBJECTIVE FUNCTION

The objective of the economic dispatch problem is to minimize the total fuel cost of thermal power plants subjected to the operating constraints of a power system. The simplified cost function of each generator can be represented as a function

$$F_T = \sum_{i=1}^{N} F_i(P_i) \tag{4.3}$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{4.4}$$

F_T -total generation cost,

F_i -cost function of generator i,

a_i ,b_i , c_i - cost coefficients of generator i,
P_i - power of generator i,
N - Number of generators.

4.3.2 EQUALITY CONSTRAINTS

Augmented Lagrange multiplier method combines the Lagrange multiplier and the penalty function methods, equality constraints are

Subjected to $h_j(X) = 0$, $j = 1, 2, \ldots\ldots\ldots\ldots p$, $p < n$ (4.5)

And equation become

$$L(X, \lambda) = f(X) + \sum_{j=1}^{p} \lambda_j h_j(X) \tag{4.6}$$

A stationary point of L(X, λ), include the equality constraints. The exterior function approach is used to define the new objective function become

$$A(X,\lambda,r_k) = f(X) + \sum_{j=1}^{p} \lambda_j h_j(X) + r_k \sum_{j=1}^{p} h_j^2(X) \qquad (4.7)$$

Where r_k is the penalty parameter. It can be shown that if Lagrange multiplier are fixed at their optimum value λ_j* in such a case there is no need to minimize the function for an increasing sequence of value of r_k since the value of λ_j* are not known in advance, an iterative scheme is used to find the solution of problem. In the first iteration the value of λ_j* are chosen as zero, the value of λ_j^* and r_k updated to start the next iteration.

$$\lambda_j^* = \lambda_j + 2r_k h_j \qquad j=1,2 \ldots\ldots\ldots\ldots p \qquad (4.8)$$

4.3.3 INEQUALITY CONSTRAINTS

In inequality constraints minimize $f(x)$

Subjected to $g_j(X) \leq 0, \qquad j = 1,2, \ldots\ldots\ldots m$ (4.9)

The inequality constraints are converted to equality constraints

$$g_j(X) + y_j^2 = 0, \qquad j=1,2,\ldots\ldots m \qquad (4.10)$$

y_j^2= slack variable. Then the augmented Lagrangian function become

$$F(X) = f(X) + \sum_{j=1}^{m} g_j(X) + \sum_{j=1}^{m} r_k [g_j(X) + y_j^2]^2 \qquad (4.11)$$

The function minimized with respect to the X and Y specification value of λ_j and r_k. This increases the problem size.

$$F(X) = f(X) + \sum_{j=1}^{m} \lambda_j \alpha_j + r_k \sum_{j=1}^{m} \alpha_j^2 \qquad (4.12)$$

Where $\alpha_j = \max\{g_j(X), -\frac{\lambda_j}{2r_k}\}$ (4.13)

In this case of equality-constrained problems using the update formula

$$\lambda_j^{(k+1)} = \lambda_j^{(k)} + 2r_k \alpha_j^{(k)} \qquad j = 1,2, \ldots\ldots..m \qquad (4.14)$$

4.3.4 MIXED EQUALITY-INEQUALITY CONSTRAINTS PROBLEMS

Consider the general optimization equation.

Minimize $f(x)$

Subjected to $g_j\,(X) \leq 0, \qquad j = 1,2, \ldots \ldots . . m$ (4.15)

$$h_j(X) = 0 \qquad j = 1,2, \ldots \ldots . . p \tag{4.16}$$

This problem solved by combining the procedure of the two preceding section.

$$F(X) = f(X) + \sum_{j=1}^{m} \lambda_j \alpha_j + \sum_{j=1}^{p} \lambda_{m+j} h_j(X) + r_k \sum_{j=1}^{m} \alpha_j^2 + r_k \sum_{j=1}^{p} h_j^2(X) \tag{4.17}$$

Value of α_j is given by eq. (4.13). The solution of the problem stated in eq. (4.15) and (4.16) found by minimizing the function A, defined by eq. (4.17) as in the case of equality constraints problems using the update formula.

$$\lambda^{(k+1)} = \lambda_j^k + 2r_k \max \{g_j(X), -\frac{\lambda_j^k}{2r_k}\} \tag{4.18}$$

$$\lambda_j^* = \lambda_j + 2r_k\, h_j(X) \qquad \text{j=1,2 ……………….p} \tag{4.19}$$

The augmented Lagrange multiplier has several advantages. As the value of r_k need not to be increased for convergence.

CHAPTER # 5

RESULTS AND DISCUSSION

In this section, the results of ED after the implementation of proposed PSO method are discussed. The programs are implemented in Matlab 6.5. The system specifications are summarized as -

Table 5.1- Data for five-unit system

Quantities	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
a_i ,$/h	25.000	60.000	100.000	120.000	40.000
b_i ,$/MWh	2.000	1.800	2.1000	2.000	1.8000
C_i ,$/(MW)^{2}h	0.008	0.003	0.0012	0.001	0.0015
$P_{i\ min}$,MW	10.000	20.000	30.000	40.000	50.000
$P_{i\ max}$,MW	75.000	125.000	175.000	250.000	300.000

5.1 COST OPTIMISATION

The objective of the DED (dynamic economic dispatch) is to schedule the outputs economically over a certain period of time under various system and operational constraints. The problem is formulated as follows

$$Min\, F = \sum_{t=1}^{T} \sum_{i=1}^{N} F_{it}(P_{it}) \tag{5.1}$$

Where F is the total operating cost over the whole dispatch period, T is the number of hours in the time horizon, N is the number dispatch able units, F_{it} (P_{it}) is the fuel cost in terms of its real power output. The thermal plant can be expressed as input output models (cost function), where the input is the electric power output of each unit and the output is the fuel cost. The fuel cost function given as follows

$$F_{it}(P_{it}) = a_i + b_i P_{it} + c_i P_{it}^2 \qquad (5.2)$$

Where ai , bi , ci , are the fuel cost coefficients of i-th unit

5.1.1 DEMAND CONSTRAINTS

$$\sum_{i=1}^{N} P_{it} - P_{Dt} = 0; \qquad t=1,2,\ldots\ldots\ldots T \qquad (5.3)$$

Where P_{Dt} is the forecasted total power demand at time t and P_{it}, the real power output at time t.

5.1.2 REAL POWER OPERATING LIMITS

$$P_{it\,min} \le P_{it} \le P_{it\,maax}, i = 1,2,\ldots N; t = 1,2,\ldots\ldots\ldots, T \qquad (5.4)$$

Where $P_{it\ min}$ and $P_{it\ max}$ are minimum and maximum real power output of generator i can supply at time t, respectively.

The effectiveness of the proposed method is tested with the five-unit system with non-smooth fuel cost function is used to demonstrate the performance of the proposed method. The system data are given in Table 5.1. The demands of the system spread over 12 intervals, are given in Table 5.2. Table 5.3 shows the DED solution by the proposed method.

Table 5.2- Load demand for 12 hours

Time ,h	Load MW	Time ,h	Load MW
1	410	7	626
2	435	8	654
3	475	9	690
4	530	10	704

5	558	11	720
6	608	12	740

In order to achieve the best performance, C_1=2 and C_2= 2, over the course of PSO run, as suggested by Y. Shi, et al [46]. Table 5.4 shows the production cost of DED solution using PSO method. Total production cost is 19636.0937 $. The given results are compared with the reference [44].

Table 5.3- Solution by PSO technique

Hour	P_1, MW	P_2, MW	P_3, MW	P_4, MW	P_5, MW	Cost
1	21.4565	84.8897	124.7865	103.0121	75.8552	1208.5597
2	9.9897	88.2611	113.4565	132.9989	90.2938	1270.1679
3	27.0112	72.1202	138.7820	132.2345	104.8521	1352.0138
4	45.2011	98.9998	135.3422	123.2397	127.2172	1480.4840
5	43.0129	106.1287	112.7593	162.2643	133.8348	1541.3287
6	50.6733	105.0334	118.4955	183.2343	150.5635	1659.7965
7	55.1238	116.2395	112.3423	198.3444	143.9500	1706.6079
8	59.1335	116.4123	113.5756	221.5869	143.2897	1776.4205
9	61.7867	123.5565	139.4457	212.5455	146.6656	1850.0151
10	56.7839	116.3940	167.8190	209.0120	153.9911	1895.1943
11	61.2355	107.9845	148.5965	224.0010	178.1825	1931.9033
12	33.6745	111.4384	127.8945	223.9840	243.0086	1971.6041

Table 5.4- Production cost using PSO

Technique	Production cost($)

PSO	19636.0937

5.2 CONCLUSION

A general PSO based dynamic economic dispatch algorithm has been developed. The effectiveness of the developed program is tested for five generator unit and 12 hours operation, and find the marginal limit of generation at define hour.

Numerical results for a sample test system have been presented to demonstrate the performance and applicability of the proposed method. Here, the solution process is independent of the fuel cost function of the generators and its convergence property is not affected by the inclusion of the inequality constraints due to the operational limits of generators.

CHAPTER # 6

CONCLUSIONS AND FUTURE WORK

6.1 CONCLUSIONS

In the PSO method, there is only one fitness value and in each iteration it moves towards the global optimal point. This makes the PSO method computationally faster. The convergence abilities of the PSO method are better than the other evolutionary methods. The PSO method converges to the global or near global point with respect to the last function.

The dynamic economic dispatch using PSO includes velocity equations, equality and inequality constraints treatment methods and creation of initial position. The application of velocity calculation in a PSO is a powerful strategy to improve the global searching ability; also the equality and inequality constraints treatment methods have always provided the solutions satisfying the constraints without disturbing the optimal process of PSO.

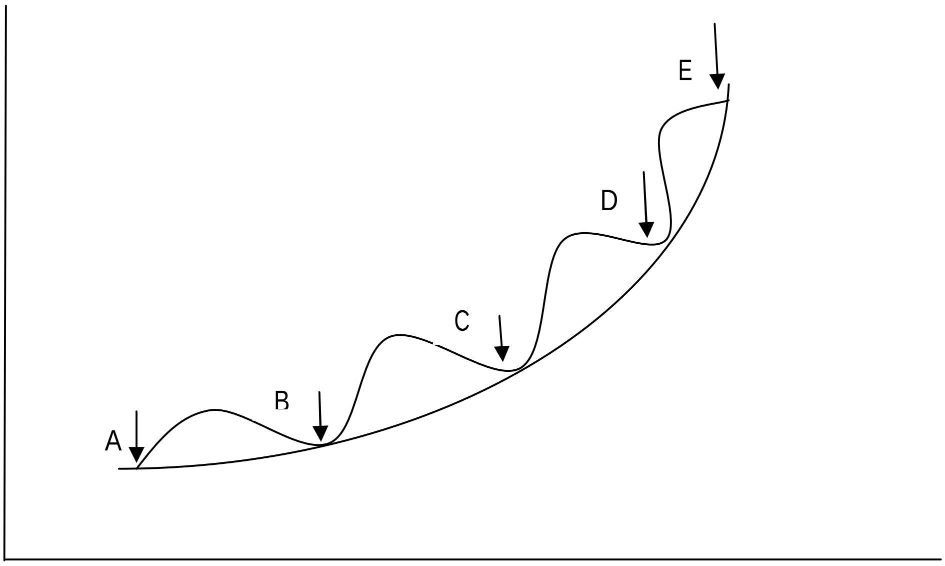
The main focus of this thesis is to survey and summarize the applications of PSO for solving the DED problems PSO based approaches. The PSO algorithm has been getting much attention in power system optimization, including marginal limit of generation. Also, for the application in the real-world ED problems, it is necessary to combine the conventional mathematical approach with the PSO methods based on their own merits. It was found to converge to optimum in a faster rate. PSO is a generalized technique and can be easily modified. The method requires primitive mathematical operators, so is computationally inexpensive in terms of both memory requirements and speed.

6.2 SCOPE FOR FUTURE WORK

6.2.1 COST FUNCTION CONSIDERING VALVE-POINT EFFECTS

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel- cost functions. Since the valve point results in the ripples as shown in Fig.-6.1, a cost function contains higher order nonlinearity. To take account for the valve-point effect, sinusoidal functions are added to the quadratic constant functions.

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + [e_1 \times \sin\left(f_1 \times \left(P_{i,min} - P_i\right)\right)] \qquad (6.1)$$



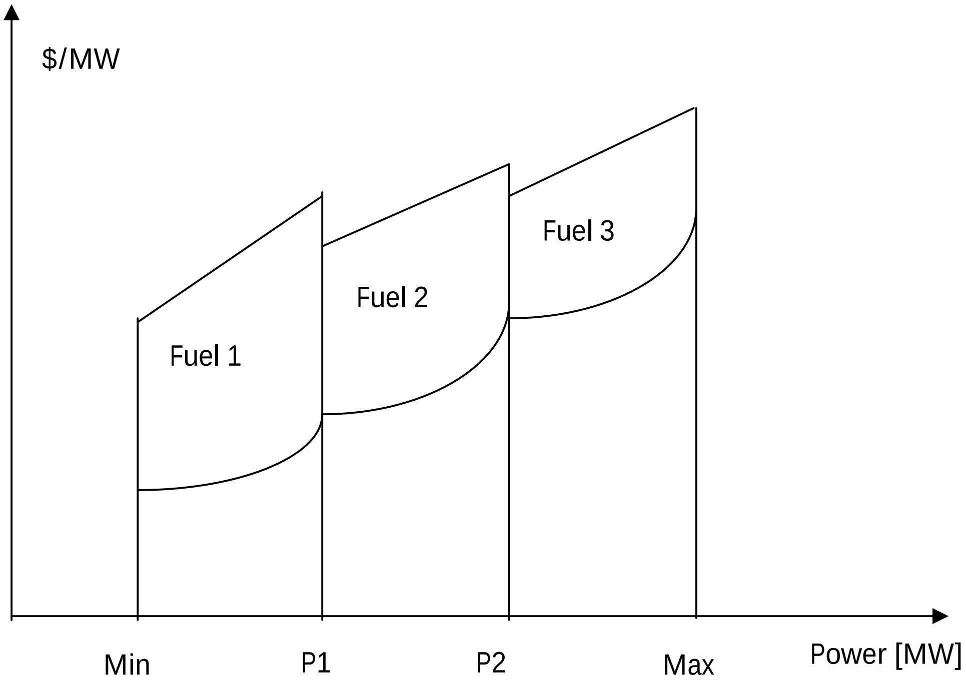
(Figure-6.1 Cost function with 5 valves)

6.2.2 COST FUNCTION WITH MULTIPLE FUELS

Since the dispatching units are practically supplied with multi-fuel sources, each unit should be represented with several piecewise quadratic functions reflecting the effects of fuel type hangs as shown in Fig.-6.2. In general, a piecewise quadratic function can be used to represent the input-output curve of a generator with multiple fuels and described as

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i\,1}P_i + c_{i_1}P_i^2 & if\ P_{imin} \le P_i \le P_{i1} \\ a_{i2} + b_{i\,2}P_i + c_{i_2}P_i^2 & if\ P_{i1} \le P_i \le P_{i2} \\ a_{i3} + b_{i\,3}P_i + c_{i_3}P_i^2 & if\ P_{i2} \le P_i \le P_{i3} \end{cases} \tag{6.2}$$

Where a_i , b_i, c_i are the cost coefficients of generator *i* for the pth power level



(Figure-6.2 Piecewise quadratic and incremental cost functions of a generator)

6.3 ECONOMIC DISPATCH PROBLEM WITH PROHIBITED OPERATING ZONES (POZ)

The economic dispatch problem which includes the effect of prohibited zones is called “economic dispatch problem with prohibited operating zones” [47]. The fuel cost function of the POZ with two prohibited operating zones is illustrated in Fig-6.3. The possible operating zones of the generators can be expressed as follows

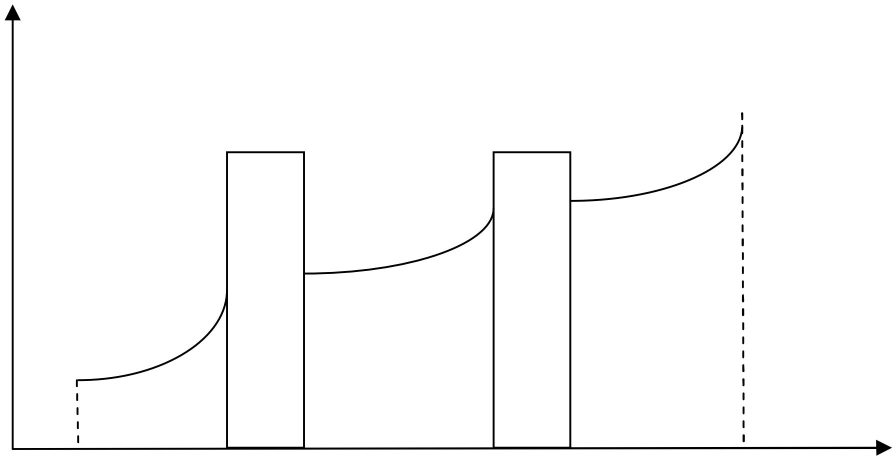
$$P_{i,min} \le P_i \le P_{i,1}^L$$

$$P_{i,k-1}^U \le P_i \le P_{i,k}^L \tag{6.3}$$

$P_{i\,n_i}^{U} \leq P_i \leq P_{i,max}$

k=2,3,…….n_i , n_i=l,........,m

Where k is the number of prohibited operating zones of generating unit i , $P_{i,k}^{L}$and $P_{i,k}^{U}$ are lower and upper limits of the kth prohibited zone of generating unit i , respectively.



(Figure-6.3 Two prohibited operating zones function cost curve)

The economic dispatch problem with prohibited operating zones the ramp rate limit constraints, prohibited operating zones constraints and transmission line losses are included.

6.4 RAMP RATE LIMIT CONSTRAINTS

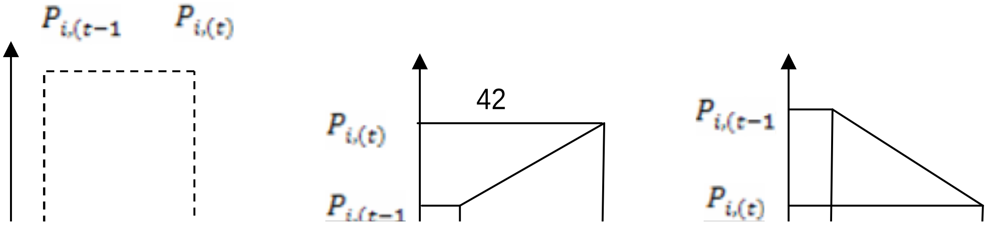
According to the operating increases and operating decreases of the generators are ramp rate limit constraints illustrated in Fig 6.4 and can be described as follow

1) as generation increases

$$P_{i,(t)} + P_{i,(t-1)} \leq UR_i \tag{6.4}$$

2) as generation decreases

$$P_{i,(t-1)} - P_{i,(t)} \leq DR_i \tag{6.5}$$



(Figure-6.4 Three feasible conditions of generating unit *i*)

Where $P_{i(t)}$ is output power of generating unit i at current and $P_{i(t-1)}$ is output power at previous. UR_i is up ramp limit of generating unit i (MW/time-period) and D_{Ri} is down ramp limit of generating unit i (MW/time-period).

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