STOCHASTIC ECONOMIC-EMISSION LOAD 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

Thapar University, Patiala

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Certificate

I hereby certify that the work which is being presented in the thesis entitled "**Stochastic Economic-Emission Load Dispatch using Particle Swarm Optimization**" in partial fulfillment of award of degree of **Master of Engineering** in **Power Systems and Electric Drives** submitted in Electrical and Instrumentation Engineering department, Thapar University, Patiala is an authentic record of my own work carried under the supervision of **Mr. Nitin Narang**, Assistant Professor, Electrical and Instrumentation Engineering department and **Mr. Nirbhow Jap Singh**, Assistant Professor, Electrical and Instrumentation Engineering department.

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

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ABSTRACT

The ELD problem in a power system is to determine the optimal combination of power outputs for all generating units which will minimize the total fuel cost while satisfying all practical constraints. Since optimum economic dispatch is not environmentally the best solution so it is required to reduce the pollution or emissions as well. Hence the classical economic dispatch problem is modified to economic-emission dispatch problem. Further, there are many inaccuracies and uncertainties in the input information which lead to deviations from optimal operation and cause an increase in the cost over the optimal value, therefore stochastic model is formed to solve the practical problem. Here, an attempt has been made to solve the stochastic economic-emission load dispatch problem using Particle swarm Optimization.

Recently evolution search techniques are used to solve ELD problem. The technique used in this thesis is Particle Swarm Optimization (PSO). There are number of applications of PSO. It has emerged as a useful tool for engineering optimization. In PSO, the behavior of each individual is affected by the best local and the best global individual to help it fly through a hyperspace. Moreover, an individual can learn from its past experiences to adjust its flying speed and direction.

In this thesis, six unit test system has been considered for economic and emission dispatch. Deviations due to unsatisfied load demand are considered as another objective function. Weighting method is used to calculate the minimum and maximum values for different objective functions. Constraints are handled as another objective while calculating the membership function. PSO search method is used to obtain the best optimal solution using fuzzy cardinal priority ranking.

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INTRODUCTION

1.1 OVERVIEW

Electric power industry is changing rapidly and under the current commercial pressure, determining the operating strategies to meet the demand for electricity, for a specific planning horizon, is one of the most important concerns. Now-a-days major challenge is to satisfy the consumer’s demand for power at minimum cost. Any given power system consisting of many generating stations, having their own characteristic operating parameters, are used to meet the total consumer demand. Usually, the cost of operating these generators is not proportional with their output, therefore the challenge for power utilities is to try to balance the total load among generators. It becomes complex when utilities try to account for the transmission loss and seasonal changes.

Economic load dispatch problem can be defined as allocating loads to plants or generators for minimum cost while meeting the various operational constraints. The generators are to be coordinated in such a way that lowest cost generators are used as much as possible and expensive generators are to be operated only when demand increases. In addition, the increasing public awareness of the environmental protection has forced the utilities to modify their operational strategies to reduce the pollution and atmospheric emissions. Hence the classical economic dispatch problem is now modified to economic-emission dispatch problem as the emission minimization has gained a lot of attention due to public demand for clean air. Practically, there are several inaccuracies and uncertainties in the input information which can lead to deviation from the optimal operation, so stochastic model is formed to solve the practical problem.

Conventional classical dispatch algorithms employing the lambda-iteration method, the base point participation factors method, and the gradient method require incremental cost curves to be of monotonically increasing nature. Unfortunately, the input-output characteristics of modern units are highly non-linear because of valve point loadings, ramp-rate limits, prohibiting operating zones etc, which results in multiple local minimum points in the cost function. So, their characteristics have to be approximated to meet the requirements of the classical dispatch algorithms. However, such approximations may lead to huge loss of expenditure over the time. Considering nonlinear characteristics of the units, solution techniques having no restrictions on the shape of the fuel cost curves are required. The classical gradient-based techniques fail in solving these types of problems [1]. Now-a-days as an alternative to the conventional mathematical approaches, modern heuristic optimization techniques such as dynamic programming, evolutionary programming, neural networks, genetic algorithm and ant colony have been given much attention by many researchers due to their ability to find an almost global optimal solution in economic dispatch problems [2].

Recently, Eberhart and Kennedy suggested a Particle Swarm Optimization (PSO) based on the analogy of swarm of bird and school of fish. In PSO, each individual makes its decision based on its own experience together with other individual's experiences [3]. The individual particles are drawn stochastically towards the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbors. The main advantages of the PSO algorithm are: simple concept, easy implementation, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques [4].

1.2 LITERATURE REVIEW

In the electric power supply systems, there exist many problems involving optimization processes. Among them, the power system scheduling is one of the most important problems in the operation and management [5]. In essence, it is an optimization problem and its main objective is to reduce the total generation cost of units, while satisfying constraints [6].

B H Chowdhry and Salfur Rahman [7] presented a survey of papers and reports which addressed various aspects of economic dispatch. The time period considered was 1977-88. This was done to avoid any repetition of previous studies which were published prior to 1977. Four very important and related areas of economic dispatch were identified and papers published in the general area of economic dispatch were classified into these: (i) Optimal power flow, (ii) economic dispatch in relation to AGC, (iii) dynamic dispatch and (iv) economic dispatch with non-conventional generation sources.

X. Xia and A. M . Elaiw [8] in their paper presented a review of the achievements of the optimal power dynamic dispatch problem. There exist two formulations for this problem in the literature. The first formulation is the optimal control dynamic dispatch (OCDD), where the power system generation has been modeled as a control system and optimization is done in the optimal control setting with respect to the ramp rates, as input variables. The second one is a later formulation known as the dynamic economic dispatch (DED), where optimization is done with respect to the dispatchable powers of the committed generation units. In this paper they first outlined the two formulations and then presented an overview on the mathematical optimization methods, Artificial Intelligence (AI) techniques, and hybrid methods used to solve the problem incorporating with extended and complex objective functions or constraints. The DED problem in deregulated electricity markets is also reported.

K S Swarup [9] presented constrained evolutionary programming algorithm approach for two distinct studies of static and dynamic economic dispatch. Multiple objective functions subjected to power flow constraints; Ramp rate limits for units, minimum and maximum allowable generations for each unit are considered.

R.B.Adler and R.Fischl [10] presented an efficient method for finding the economic and steady-state secure base point generation levels to supply the present load. The base points are calculated using a linear but lossy system model coupled with an efficient gradient computation technique. The worst case bus load condition is found as an extension of the base point calculation.

J.S.Al-Sumait *et al.* [11] presented a new approach based on a constrained PS algorithm to solve various types of power system economic load dispatch (ELD) problems. These problems include economic dispatch with valve point (EDVP) effects, multi-area economic load dispatch (MAED), companied economic-environmental dispatch (CEED), and cubic cost function economic dispatch (QCFED).

Kyung-Il Min *et al.* [12], in their paper presented a novel approach to economic dispatch (ED) with non-convex fuel cost function as combinatorial optimization problems while most of the conventional researches have been developed as function optimization problems. One non-convex fuel cost function can be divided into several convex fuel cost functions, and each convex function can be regarded as a generation type. In that case, ED with non-convex fuel cost function can be considered as combinatorial optimization problems, finding the best case among all feasible combinations of generation types. This paper deals with three kinds of ED problems, namely ED considering valve-point effects (EDVP), ED with multiple fuel units (EDMF), and ED with prohibited operating zones (EDPOZ).

S. Khamsawang and S. Jiriwibhakorn [13] proposed an application of the differential evolution (DE) algorithm for solving the economic dispatch problem (ED). Furthermore, the regenerating population procedure added to the conventional DE in order to improve escaping the local minimum solution.

Ahmed farag *et al.*[14] described a novel efficient method and algorithm to obtain the optimal shift in power dispatch related to contingency states or overload situations in power system operation and planning phases under various objectives such as economy, reliability and environmental conditions. The optimization procedures basically utilize linear programming with bounded variables and it incorporates the techniques of the Section Reduction Method and the Third Simplex Method.

Vo Ngoc Dieu and Weerakorn Ongsakul [15] proposed an augmented Lagrange Hopfield network (ALHN) for solving economic dispatch (ED) problem with ramp rate, emission and transmission constraints. The proposed ALHN method is the continuous Hopfield neural network with its energy function based on augmented Lagrangian function. Consequently, ALHN can overcome the drawbacks of the conventional Hopfield network due to its simplicity, better optimal solution and faster computing time.

James Kennedy and Russell Eberhart [16] introduced a concept for the optimization of nonlinear functions using particle swarm methodology is introduced. The evolution of several paradigms is outlined, and an implementation of one of the paradigms is discussed. Benchmark testing of the paradigm is described, and applications, including nonlinear function optimization and neural network training, are proposed. The relationships between particle swarm optimization and both artificial life and genetic algorithms are described.

A. Lakshmi Devi and O. Vamsi Krishna [17] in their paper proposed a lambda based approach for solving the Combined Economic and Emission Dispatch (CEED) problem using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) methodologies considering the power limits of the generator.

Amita Mahor *et al.* [18] summarized the application of PSO in ED problem, which is considered as one of the most complex optimization problem. Practical economic dispatch (ED) problems have nonlinear, non-convex type characteristics with intense equality and inequality constraints. The conventional optimization methods are not able to solve such problems due to local optimum solution convergence. Metaheuristic optimization techniques especially particle swarm optimization (PSO) has gained an incredible recognition as the solution algorithm for such type of ED problems in last decade.

K. Sathish Kumar *et al.* [19] in their paper developed an efficient and clear insight view about the application of various PSO algorithms to the economic load dispatch problem with emission restrictions as the constraint. Solution acceleration techniques in the algorithm which enhance the speed and robustness of the algorithm are developed. The power and usefulness of the algorithm is demonstrated through its application to a test system.

Jong-Bae Park *et al.* [20] presented a modified PSO (MPSO) mechanism to deal with the equality and inequality constraints in the ED problems. A constraint treatment mechanism is devised in such a way that the dynamic process inherent in the conventional PSO is preserved. Moreover, a dynamic search-space reduction strategy is devised to accelerate the optimization process.

K. Sathish Kumar *et al.* [21] in their paper applied four modified versions of particle swarm optimizer (PSO) to the economic power dispatch with valve-point effects. The different PSO techniques are New PSO, Self Adaptive PSO and Chaotic PSO. Among the different PSO techniques, it is found that Self-Adaptive PSO is better than other PSO techniques in terms of better solution, speed of convergence, time of execution and robustness but it has more premature convergence.

Jong-Bae Park *et al.* [22] presented a novel and efficient method for solving the economic dispatch (ED) problems with valve-point effect, by integrating the particle swarm optimization (PSO) with the chaotic sequences.

Vivani and Heydt [23] have outlined the computational details of the stochastic optimal energy dispatch problem. The algorithm for this problem employed the multivariate Gram-Charlier series to statistically model the probability density function of the control vector. The applicability of the series has been limited by high computational requirements of calculating high order statistically moments. The main aim of the method was to produce a tool which would be useful from an operational standpoint but failed to consider cost function.

Yakin [24] has articulated an approach to the optimal generation scheduling by treating the electricity demand at a node as a random variable with a known probability distribution. A two-stage stochastic programming with recourse model has been developed for stochastic economic dispatch. An equivalent problem to this two-stage model has been defined. The penalties for discrepancies in the generation have been included in the objective function of the equivalent problem. The major difficulty during the implementation is to draw out the exact values of these penalties.

El-Harway and Mbamalu [25] have investigated the perturbations in the system thermal fuel cost and the system equality constraints at stochastic and normally distributed with zero mean and a given variance. **El-Harway and Mbamalu** [26] introduced a combined quasi-Newton and conjugate gradient technique, in which the system power demand was assumed random with zero mean and unit variance. **El-Harway and Mbamalu** [27] considered the perturbations in system power demand as random and normally distributed with zero mean and some variance. They observed that optimally conditions in terms of the active power generations were biased by parameters obtained from the variances of active power generations. But these methods do not provide trade-off between economy and risk measure due to uncertainties in system production cost and randomness of demand.

S. C. Parti [28] has expounded an economic dispatch of thermal generation while incorporating the randomness in system production cost and system load through generator outputs, which were treated as random variables. He appended the traditional objective function of economic dispatch with a penalty term accounting for the possible deviations proportional to the expectations of the square of unsatisfied load because of randomness of generator power. This approach suppresses the true character of the problem by considering only the monetary aspects and fails to express the non-commensurability of the conflicting objectives.

S. K. Bath *et al.* [29] explored the use of genetic algorithm to search for the assigned weight pattern of objectives to obtain the best compromised thermal power generation schedule in the multi-objective framework. The multi-objective problem is formulated considering non-commensurable objectives viz. operating cost, NO_x emission, and variance of real, as well as reactive, power generation mismatch with explicit recognition statistical uncertainities in the thermal power generation cost curves, emission curves, and power demands, which are considered random variables. The solution set of such formulated problem is non-inferior due to contradictions among the objectives taken.

1.3 OBJECTIVE OF THESIS

The objective of the thesis is to study and work on Stochastic Economic-Emission Load dispatch problem, thereby minimizing the expected fuel cost, expected NO_x emissions and expected deviations due to unsatisfied load demand subject to equality and inequality constraints.

1.4 ORGANISATION OF THESIS

The work carried out has been organized into six chapters.

Chapter 1 includes overview of the thesis, literature review. It also includes objective of the work and organization of the thesis.

Chapter 2 presents a brief introduction to economic-emission load dispatch and then brief introduction is given for stochastic multi-objective optimal power dispatch.

Chapter 3 gives introduction to Particle Swarm Optimization and the various steps involved in its implementation. It also includes advantages and disadvantages of PSO.

Chapter 4 describes stochastic economic-emission load dispatch using PSO. It discusses the solution approach to the problem with its algorithm and decision making to the problem with flow-chart.

Chapter 5 describes the results and discussions pertaining to various cases.

Chapter 6 concludes the work done with future scope.

CHAPTER 2

STOCHASTIC MULTI-OBJECTIVE GENERATION SCHEDULING

2.1 INTRODUCTION

The conventional economic load dispatch problem of power generation involves allocation of power generation to different thermal units to minimize the operating cost subject to intense equality and inequality constraints of the power system. Thus the economic load dispatch problem becomes a large-scale highly non-linear constrained optimization problem. However, as a result of public awareness of environmental protection, diverse emission compliance strategies have emerged [30]. These strategies include emission dispatching, fuel switching, installation of emission reduction equipment in the existing thermal plants, and retirement of old fuel-burning equipment or generating unit and replacement with cleaner and efficient one. Among these strategies, unit dispatch considering emission and cost minimization have received widespread attention due to its effective short-term results and smaller capital outlay.

In addition, thermal power optimization directly influences the power system stability and power quality and helps in obtaining the objective of minimizing the total system real power loss in the transmission network. Thus, the economic load dispatch considering system loss can reasonably improve thermal power dispatch simultaneously. So, the economic load dispatch problem considering economic, environment and system loss can be handled as a multi-objective optimization problem with non-commensurable and contradictory objectives [31].

Although there are many uncertainties arising in power system operations, the typical formulation of planning and scheduling power generation activities remains deterministic. It is implicitly assumed that the problem is refrained from both intrinsic and extrinsic disturbance and inaccuracy. However, many-a-times this ideal assumption is not true in real-world applications, and the deviations are even quite considerable in certain conditions. The uncertainties may come from the internal parameter changes as well as the external parameters such as load demands. In this thesis, the multiple objectives in the environmental/economic power dispatch and their associated constraints are presented. In the problem formulation, the fuel cost coefficients, emission coefficients, and load demand are considered as random variables, which are uniformly distributed and dependent on one another [32].

2.2 INTORDUCTION TO ECONOMIC-EMISSION LOAD DISPATCH

The objective function of the economic dispatching problem is to define the production level for each plant so that the total cost of generation and transmission is minimum for the prescribed schedule of loads.

Electrical energy cannot be stored, but is generated from natural sources and delivered as demand arises. For the delivery of bulk power over considerable distances, a transmission system is used, and for local deliveries a distribution system is used. Utilities can exchange power, share reserves and render assistance to one another in times of need by the transmission networks which are interconnected through ties. For an interconnected system, the fundamental problem is of minimizing the source expenses [33].

Also the efficient use of the available fuel is growing in importance, both monetarily and because most of the fuel used represents irreplaceable natural resources. The efficient and optimum economic operation and planning of electric power generation systems have always occupied an important position in the electric power industry [34]. The solution of economic dispatch problem will give the amount of power to be generated by various generating units of a power system for a minimum total fuel cost.

But in this problem limitation on emission release is not considered. The emission of pollutants affects not only human beings, but is also harmful to other life forms. It is also responsible for the damage to materials and cause global warming. These effects may be interpreted as cost, as they degrade the environment in one or other form. The objective of emission dispatch is to minimize the total environmental degradation or the total pollutant emission due to the burning of fuels for production of power to meet the load demand.

2.2.1 Generator Operating Cost

The majority of generators in extant systems are of three types: nuclear, hydro, and fossil (coal, oil or gas). Simple model of fossil plant is given in fig. 2.1 which consists of boiler, turbine and generator. Nuclear plants are operated at constant output levels and there are essentially no variable operating costs in hydro plants. Therefore, the components of cost which comprise the dispatching procedures are the cost of fuel burnt in the fossil plants. 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 generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [35].As the unit loading increases, the input to the unit increases and the incremental heat rate decreases between the opening points for any two valves. However, when a valve is first opened, the throttling losses increase rapidly and the incremental heat rate rises suddenly. This gives rise to the discontinuous type of incremental heat rate characteristic as shown in fig.2.2 [34]. 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 in a valve are large when a valve is just opened and small when it is fully opened.

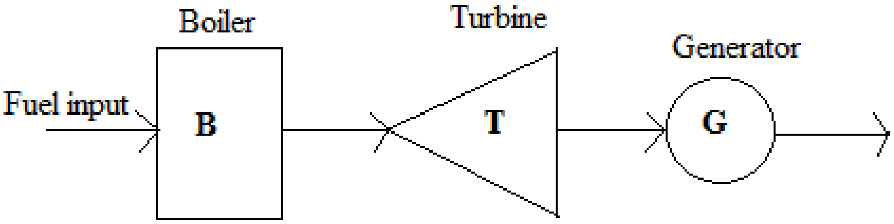


Fig.2.1 Simple model of fossil plant

For dispatching purposes, this 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

$$F_1 = a_i P_i^2 + b_i P_i + c_i \quad Rs/hr \tag{2.1}$$

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 [33].

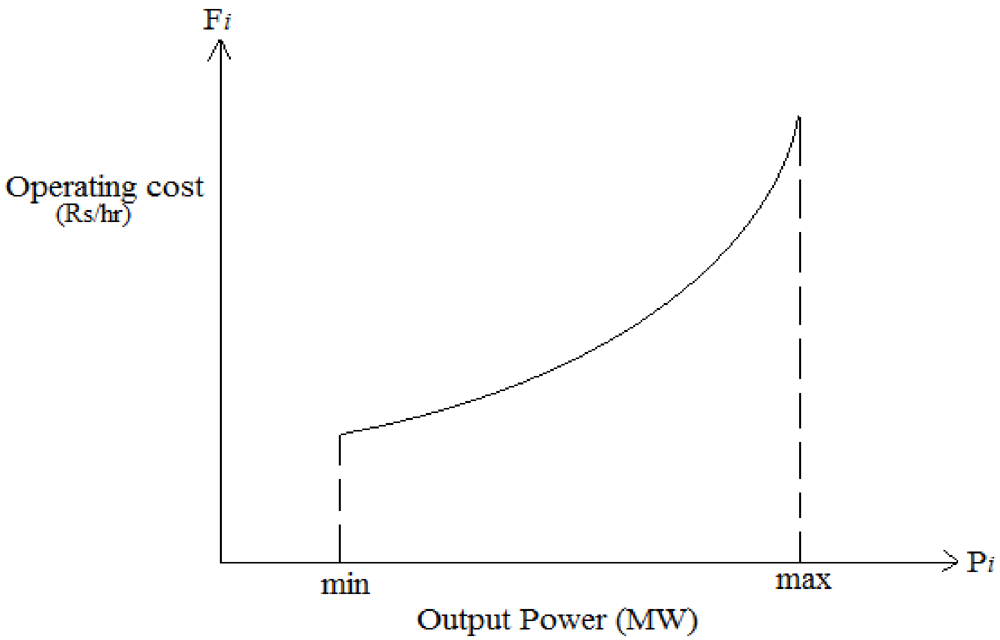


Fig 2.2 Operating costs of a fossil-fired generator

P_i^{min} is the minimum loading limit below which it is uneconomical (or may be technically infeasible) to operate the unit and P_i^{max} is the maximum output limit.

In reality, because of valve-point effects, there are non differentiable points in the objective function of an economic dispatch problem. Therefore, the objective function should be composed of a set of non-smooth cost functions [36]. This type of input-output characteristic is non-convex. Hence optimization techniques that require convex characteristics may not be used [34].

The valve opening process of multivalve steam turbines produces a ripple-like effect in the heat rate curve of the generators, and it is taken into consideration in the ED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoidal component as follows: [37]

$$F_1 = \sum_{i}^{NG} \Big(a_i P_i^2 + b_i P_i + c_i \ \ + | \, \eta_i * \sin \{ \, \gamma_i * (P_i^{min} - \ P_i \Big) \, | \qquad Rs/hr \qquad (2.2)$$

Where η_i and γ_i are the coefficients of generator 'i' reflecting valve-point effects.

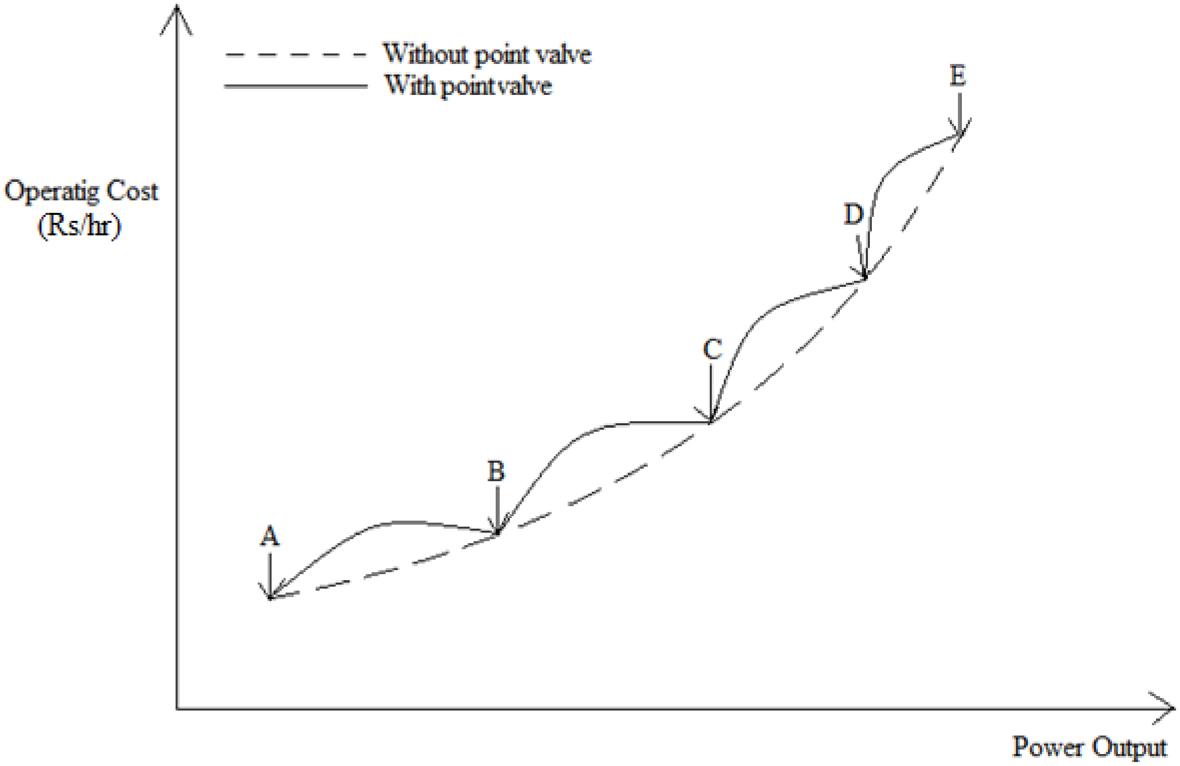


Fig.2.3 Operating cost characteristics with valve point loading.

Operating cost characteristics with and without valve point loading are shown in fig. 2.3, here dotted line represents the characteristics without valve point loading.

2.2.2 Emissions

In traditional economic dispatch, the operating cost is reduced by proper allocation of the amount of power to be generated by different generating units. However the optimum economic dispatch may not be the best considering the environmental aspect. Recently many countries throughout the world have concentrated on the reduction of the amount of pollutants from fossil fuel power generating units. Apart from particulate pollutants, there are three gaseous pollutants namely carbon dioxide, sulphur oxides and nitrogen oxides emitted from fossil fuel power plants.

The economic dispatch and emission dispatch are considerably different. The economic dispatch reduces the total fuel cost i.e. operating cost of the system at an increased rate of NO_x. On the other hand emission dispatch minimizes the total emission from the system by an increase in the system operating cost. Therefore it is necessary to find out an operating point, that strikes a balance between cost and emission. This is achieved by combined economic and emission dispatch (CEED).

There are two sources of nitrogen that combine with oxygen from the fuel and the combustion air to produce NO_x. The first source is nitrogen in the air that produces emission called thermal NO_x. The second source is nitrogen in the fuel that produces emission called fuel NO_x. The total NO_x produced during combustion is the sum of the thermal NO_x and fuel NO_x. In coal, there is no apparent correlation between the amount of fuel bound nitrogen and the fuel NO_x produced [19].

The emission dispatch problem for NO_x emission can be defined as the following optimization problem:

Minimize

$$F_2 = \sum_{i=1}^{NG} (d_i P_i^2 + e_i P_i + f_i) \tag{2.3}$$

where $d_i, e_i, and\ f_i$ are the cost coefficients and

NG is the number of generating units.

2.3 STOCHASTIC LOAD DISPATCH

In the optimal economic dispatch procedure, total generation required is allocated among the available generating units in the system in such a way that the constraints imposed on different system variables are adequately satisfied and the achieved overall cost associated with it is a minimum.

Despite extensive research focusing on thermal power dispatch problem, much of the focus has been on the development of deterministic models applicable to steady-state conditions. It means that all input information is known with complete certainty and the optimal plans of dispatch are always realized exactly. Practically there are several inaccuracies and uncertainties in the input information, which lead to deviations from optimal operation [38].

In the recent years, with the more attention drawn towards the protection of environment, now-a-days environmental/economic dispatch (EED) is being preferred for reducing the emission. It turns out to be a more desired power dispatch scheme with respect to the previous pure economic dispatch approaches. However, most of these studies use the deterministic models, which are not applicable practically. Due to the inaccurate and uncertain information such as forecast and measurement errors, the production costs are usually random variables. In real-world system operations, the load demand is also considered as a random variable. Therefore, it is highly necessary to construct the stochastic model, based on which various power dispatch strategies can then be developed [32].

The operating cost functions which represent the performance characteristics of thermal plants are computed by calculating the overall thermodynamic performance of a unit consisting of boiler, turbine, condenser, heat cycle, and associated plant auxiliaries. In most of the cases these cost functions are inaccurate. The reasons responsible for the inaccuracies are summarized in fig. 2.4 and are listed below [38].

- Inaccuracies in the process of measuring the basic data used for computation of thermodynamic performance of the unit.
- Because of the errors encountered in operation due to operating at other than standard pressure and temperature, deviations may be observed from the computed thermodynamic performance of the unit.
- Effect of time on equipment conditions which influences some of its operating characteristics, notably its efficiency.
- Inaccuracies resulting from inability to hold generation at exact desired output.
- Fuel cost variations.
- Load forecasting errors.
- Inaccuracies introduced by various types of transmission loss equations.

Further, because of great difficulty in determining the dependency of maintenance costs from the power output, the additional costs for maintenance, supplies and water are very inaccurate. In the steady-state operation, inaccuracies of great magnitude will be caused if all these factors are taken together. The effect of inaccuracies leads to an increase in the overall cost.

In general, a large-scale system as typified by an electric power system possesses multiple objectives to be achieved, namely economic operation, reliability, security and minimal impact on environment. It may be obvious that trade-offs among these objectives are difficult because of their different nature. This implies that objectives are non-commensurable [33].

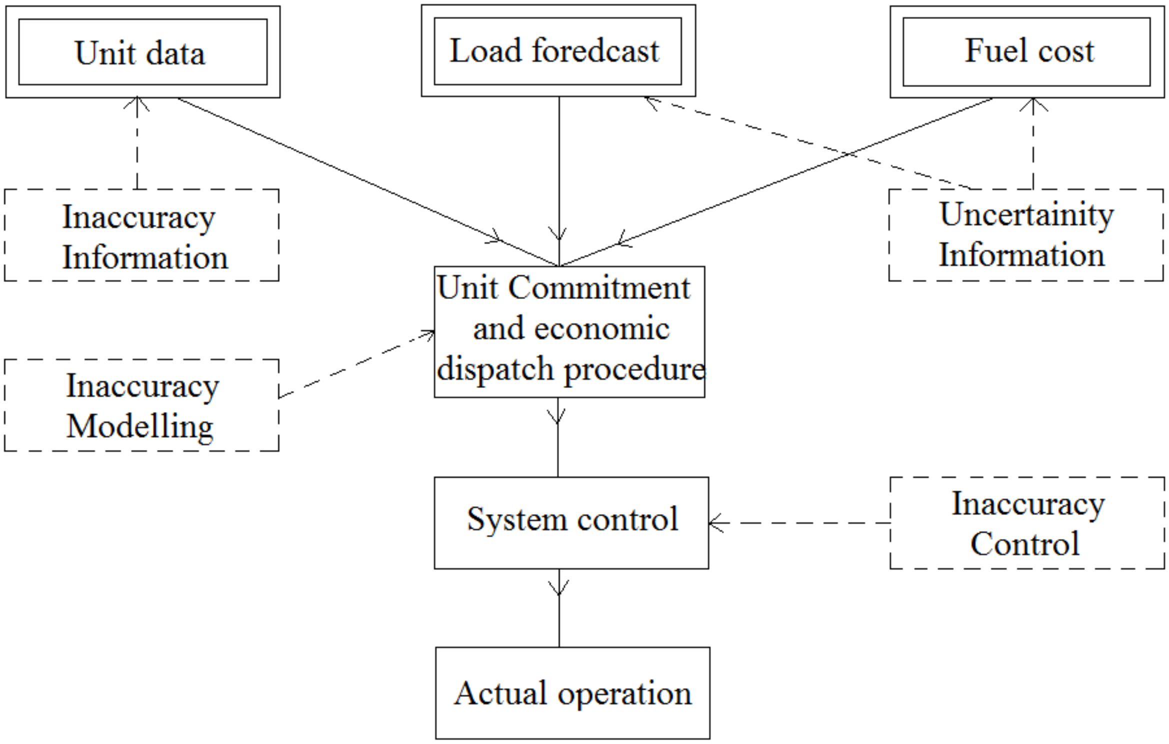


Fig.2.4 Optimal Power system operation: inaccuracies and uncertainties

So deterministic models are however not able to reflect some real situations in practical applications due to certain inaccurate and uncertain factors which are uniformly involved in system operations. Therefore stochastic models are more suited to be used for investigating some of the power dispatch problems [32].

2.4 MULTI-OBJECTIVE STOCHASTIC OPTIMAL THERMAL POWER DISPATCH

The economic dispatch problem was defined so as to determine the allocation of electricity demand among the committed generating units to minimize the operating costs subject to physical and technological constraints. Most of the existing formulations of the economic dispatch problem are solved as static deterministic optimization problems. But practically there are many inaccuracies and uncertainties in the input information which lead to deviations from optimal operation and cause an increase in the cost [40]. As a result of the rise in production costs due to numerous uncertain factors, the electric energy system has been represented as a network characterized by random variables and investigated by numerous researchers at various levels[41][42][27].

2.4.1 Stochastic Economic-Emission Problem Formulation

In this section, the multi-objectives with the equality and inequality constraints in relaition to the power system optimization problem are described. The important non-commensurable objectives taken into account are:

- Economic operation
- Minimal impacts on environment
- Expected deviations due to unsatisfied load

The stochastic economic emission formulation is formed by considering fuel cost coefficients, emission coefficients and load demand as random variables. The stochastic models can be converted to their deterministic equivalents by taking their expected values, with the assumption that all the random variables are uniformly distributed and statistically dependent on each other.

2.4.1.1 Expected Fuel Cost

The objective function to be minimized is the total operating cost for thermal generating units in the system and a quadratic operating cost curve is assumed.

$$F_1 = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + c_i) \tag{2.4}$$

Where

$a_i,\ b_i, and\ c_i$ are the cost coefficients.

NG is the number of generating units.

A stochastic model of functionF_1, is formulated by considering cost coefficients and load demand as random variables. By taking expected values, the stochastic model can be converted into its deterministic equivalent. The random variables are assumed to be normally distributed and statistically dependent on each other. The expected value of operating cost function may be obtained by expanding the functions using Taylor’s series, about mean [43]. By taking the expectation of the expanded form, the expected operating cost function is represented by:

$$\bar{F}_1 = \sum_{i=1}^{NG} [\bar{a}_i \, \bar{P}_i^2 + \bar{b}_i \bar{P}_i + \bar{c}_i + \bar{a}_i var(P_i) + cov(b_i, \, P_i) + 2\bar{P}_i cov(a_i, \, P_i)] \tag{2.5}$$

where

$\bar{P}_i$ is expected power generation of the i^{th} generator.

$\bar{a}_i, \bar{b}_i \; and \; \bar{c}_i$ are expected cost coefficients.

In this study, variance and covariance are replaced by coefficient of variation (CV) and correlation coefficient (CC), respectively. In general, variance and covariance are defined as

$$var(X) = C_X^2 \overline{X^2} \tag{2.6}$$

$$cov(X, Y) = R_{XY} C_X C_Y \bar{X} \bar{Y} \tag{2.7}$$

where

$C_X \; and \; C_Y$ are the CV of random variables X and Y, respectively.

R_{XY} is the CC of random variables X and Y.

The value of CC is positive or negative depending upon the sign of the covariance and its value lies between -1.0 and 1.0.

Using Eq. (2.6) and (2.7), Eq. (2.5) can be rewritten in simplified form as

$$\bar{F}_1 = \sum_{i=1}^{NG} [(1 + C_{P_i}^2 + 2R_{a_i P_i} \, C_{a_i} C_{P_i}) \bar{a}_i \bar{P}_i^2 + \left(1 + R_{b_i P_i} C_{b_i} C_{P_i}\right) \bar{b}_i \bar{P}_i + \bar{c}_i \tag{2.8}$$

2.4.1.2 Expected NO_x Emission

The emission curve can be directly related to the cost curve through the emission rate per Mkcal, which is a constant factor for a given type of fuel. Therefore, the amount of NO_x emission is given as a function of generator output P_i , which is quadratic, i.e.

$$F_2 = \sum_{i=1}^{NG} \left(d_i P_i^2 + e_i P_i + f_i \right) \tag{2.9}$$

where d_i, e_i and f_i are emission coefficients.

A stochastic emission model is formulated by considering emission coefficients and load demand at random. Using Taylor's series and taking the expectation, the expected NO_x emission is obtained as

$$\bar{F}_2 = \sum_{i=1}^{NG}[\bar{d}_i \bar{P}_i^2 + \bar{e}_i \bar{P}_i + \bar{f}_i + \bar{d}_i var(P_i) + cov(e_i, P_i) + 2\bar{P}_i cov(d_i, P_i)] \tag{2.10}$$

where

$\bar{d}_i, \bar{e}_i$ and $\bar{f}_i$ are expected emission coefficients.

Rewriting the above equation as

$$\bar{F}_2 = \sum_{i=1}^{NG}[(1 + C_{P_i}^2 + 2R_{d_iP_i} C_{d_i} C_{P_i})\bar{d}_i \bar{P}_i^2 + \left(1 + R_{e_iP_i} C_{e_i} C_{P_i}\right)\bar{e}_i \bar{P}_i + \bar{f}_i \tag{2.11}$$

Where

C_{d_i} is the coefficient of variation of random variable d_i.

C_{e_i} is the coefficient of variation of random variable e_i.

$R_{d_iP_i}$ is the correlation coefficient of the random variables d_i and P_i.

$R_{e_iP_i}$ is the correlation coefficient of the random variables e_i and P_i.

2.4.1.3 Expected deviations

Since generator outputs powers are treated as random variables, the expected deviations are proportional to the expectation of the square of the unsatisfied load demand. These expected deviations are considered as the third objective to be minimized. The third objective function $\bar{F}_3$ is represented as

$$\bar{F}_3 = E[(\bar{P}_D + \bar{P}_L - \sum_{i=1}^{NG} \bar{P}_i)^{\mathbf{2}}] \tag{2.12}$$

This on simplification reduces to

$$\bar{F}_3 = \sum_{i=1}^{NG} var(P_i) + \sum_{i=1}^{NG-1} \sum_{j=i+1}^{NG} 2cov(P_i, P_j) \tag{2.13}$$

$$\bar{F}_3 = \sum_{i=1}^{NG} C_{P_i}^2 \bar{P}_i^2 + \sum_{i=1}^{NG} \sum_{\substack{j=1 \\ j \neq i}}^{NG} R_{P_i,P_j} C_{P_i} C_{P_j} \bar{P}_i \bar{P}_j \tag{2.14}$$

2.4.1.4 Expected Transmission Loss

The transmission power loss expressed through the simplified well known loss formula expression as a quadratic function of power generation is given by [44]:

$$P_L = B_{00} + \sum_{i=1}^{NG} B_{i0} P_i + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i \, B_{ij} \, P_j \quad MW \tag{2.15}$$

where

Power generations P_i are dependent random variables.

B_{ij} are also considered as inaccurate B-coefficients.

The expected transmission losses using Taylor’s series are represented as

$$\bar{P}_L = \sum_{i=1}^{NG} \sum_{j=1}^{NG} \bar{P}_i \, \bar{B}_{ij} \bar{P}_j + \sum_{i=1}^{NG} \bar{B}_{ii} \, var(P_i) + \sum_{i=1}^{NG-1} \sum_{\substack{j= \\ i+1}}^{NG} 2\bar{B}_{ij} cov(P_i, P_j) + \sum_{i=1}^{NG} 2\bar{P}_i cov\,(P_i, B_{ii})$$
$$+ \sum_{i=1}^{NG} \sum_{\substack{j=1 \\ j \neq 1}}^{NG} 2\bar{P}_j \, cov(P_i, B_{ij}) \tag{2.16}$$

On simplification the above equation can be rewritten as

$$\bar{P}_L = \sum_{i=1}^{NG} [(1 + C_{P_i}^2 + 2R_{P_i B_{ii}} C_{P_i} C_{B_{ii}}) \bar{B}_{ii} \bar{P}_i^2 + \sum_{i=1}^{NG} \sum_{\substack{j= \\ i+1}}^{NG} [1 + R_{P_i,P_j} C_{P_i} C_{P_j}$$
$$+ 2R_{P_i B_{ij}} C_{P_i} C_{B_{ij}}] \bar{P}_i \bar{B}_{ij} \bar{P}_j \tag{2.17}$$

where

$\bar{B}_{ij}$ are expected B-coefficients.

$R_{P_i B_{ij}}$ are the correlation coefficients of random variables $P_i \; andB_{ij}$.

$C_{B_{ij}}$ are the coefficients of variation of uncertain parameter B_{ij}.

The deterministic equivalent of multi-objective stochastic optimization problem is formulated by taking (a) expected fuel cost, (b) expected NO_x emission and (c) expected deviations due to unsatisfied load demand, which are to be minimized, while satisfying the expected equality and inequality constraints.

Mathematically the problem can be formulated as:

Minimize

$$[\bar{F}_1, \bar{F}_{2,} \bar{F}_3]^T \tag{2.18}$$

Where $\bar{F}_1, \bar{F}_{2,}\ and\ \bar{F}_3$ are the expected values of objective functions to be minimized over the set of admissible decision variables $\bar{P}_i$.

Subject to:

a) The energy balance equation

For real power balance, an equality constraint should be satisfied. The total generated power should be equal to total load demand plus the total losses.

$$\sum_{i=1}^{NG} \bar{P}_i = \bar{P}_D + \bar{P}_L \tag{2.19}$$

b) The inequality constraints

There is a unit operating limit on the amount of power which a unit can deliver. The power output of any unit should not exceed its rating nor should it be below that necessary for stable operation. Generation output of each unit should lie between maximum and minimum limits. The corresponding inequality constraints for each generator are [45].

$$\bar{P}_i^{min} \leq \bar{P}_i \leq \bar{P}_i^{max} \qquad (i = 1,2, \ldots ., NG) \tag{2.20}$$

where

$a_i,\ b_i, and\ c_i$ are the cost coefficients.

$\bar{P}_D$ is the expected total demand.

$\bar{P}_i$ is the expected real power generation and will act as decision variable.

NG is the number of generating units.

$\bar{P}_L$ is the expected transmission power loss.

CHAPTER 3

PARTICLE SWARM OPTIMIZATION

3.1 INTRODUCTION

Particle Swarm Optimization (PSO) was first proposed by Kennedy and Eberhart in 1995 [44]. This technique was inspired by the choreography of a bird flock, which can be seen as a distributed behavior algorithm that performs multidimensional search [46]. In a flock of birds or a school of fish, if one individual finds a good way to move for the food or protection, other members in the swarm follow its movement promptly. This process can be modeled by a swarm of particles moving in the multidimensional search space, each of which has a position and a velocity. These particles flying across the hyperspace, record the best positions which they have ever encountered. Members of a swarm adjust their velocities and positions by communicating desirable positions to one another [32].

3.2 CONCEPT OF SWARM AND PARTICLE

The term *swarm* has a basis in the literature. In particular, the authors use the term in accordance with a paper by Millonas [47], who developed his models for applications in artificial life, and articulated five basic principles of swarm intelligence.

- *Proximity principle*: According to this principle, the population should be able to carry out simple space and time computations.
- *Quality principle*: According to this principle, the population should be able to respond to quality factors in the environment.
- *Principle of diverse response*: According to this principle, the population should not commit its activities along excessively narrow channels.
- *Principle of stability*: According to this principle, the population should not change its mode of behavior every time the environment changes.
- *Principle of adaptability*: According to this principle, the population must be able to change behavior mode when it’s worth the computational price.

The term *particle* was selected as a compromise. The population members are mass-less and volume-less, and thus could be called “points”, it is felt that velocities and accelerations are more appropriately applied to particles, even if each is defined to have arbitrarily small mass and volume [19].

3.3 PSO AS AN OPTIMIZATION TOOL

PSO can be used as an effective optimization tool to handle the optimization problems which cannot be easily solved by the traditional analytical approaches. As an optimizer, PSO provides a population-based search procedure. Each single particle can be assumed as a “bird” in the search space. Particles flying in the multidimensional space adjust their position based on both its own experience and that of their neighboring companions. In this way, PSO combines local search with global search for balancing the exploration and exploitation [32]. To adjust its flying speed and direction, an individual can learn from its past experiences. Therefore, all the individuals in the swarm can quickly converge to near-optimal geographical positions with well-preserved population density distribution by observing the behavior of the flock and memorizing their flying histories.

Normally, PSO is considered as an evolutionary computation approach as there are many common characteristics between evolutionary algorithms and PSO such as:

1) It is initialized with a population of random solutions.

2) It searches for the optimum values by updating generations.

3) The adjustments of individuals are analogous to real value crossover operation in evolutionary algorithms.

4) Fitness evaluation is evaluated by objective functions.

However, unlike EAs, the updates of the individuals of PSO are not accomplished by random crossover or mutation of genes. In PSO, an equation is used to calculate the new velocity of each individual j at the i_{th} dimension based on its current location P_{ij} , previous velocity (V (i, j)), previous location (*pbest* (i, j)), where the best fitness this individual has achieved the best fitness, and the population’s best global location (*gbest* (i)), where the best fitness value the entire population has achieved. Therefore, the velocity updating equation is

$$V_{ij}^{new} = w \times V_{ij} + C_1 \times rand() \times \left(P_{ij}^{best} - P_{ij}\right) + C_2 \times rand() \times \left(G_i^{best} - P_{ij}\right) \qquad (3.1)$$

where

w is an inertia weight value and

$rand()$ is the random numbers between 0 and 1.

C_1 and C_2 are acceleration factors.

P_{ij}^{best} is that best position for individual particle which yields lowest cost over all generations.

G_i^{best} is the location of best particle in the entire population of all generations.

After the velocity is updated, the new location of j_{th}individual at the i_{th} dimension can be calculated as

$$P(i,j) = P(i,j) + V\,(i,j) \qquad (3.2)$$

Comparing with evolutionary algorithms, PSO's information sharing mechanism is significantly different. In EAs, individuals share their information with each other by crossover and the whole population moves like one group towards an optimal point. In PSO, only *gbest* (*i*) provides the information to other individuals to adjust their speeds. It is a one-way information sharing mechanism [48]. The entire population follows the movement of the best individual and converges to a *near-optimal* solution quickly.

3.4 VARIOUS STEPS INVOLVED IN THE IMPLEMENTATION OF PSO:

- **Implementation**

The main objective of economic dispatch is to obtain the amount of real power to be generated by each committed generator, while achieving a minimum generation cost within the constraints. The particle swarm optimization is implemented by searching the generation of power plants, P_i within generator limits. The economic dispatch problem and transmission losses are defined in previous chapter. This section provides the solution methodology to the economic dispatch problems using PSO.

➢ Representation of the Swarm

Swarm is formed by the real power generations which are the decision variables of the economic dispatch problems. Position of the particles in the swarm is represented by the set of real power output of all the generators. For a system with NG generators, the particle position is represented as a vector of length NG. If there are NP particles in the swarm, the complete swarm is represented as a matrix as below:

$$Swarm = \begin{bmatrix} P_{12} & P_{12} & .. & .. & P_{1NG} \\ P_{21} & P_{21} & .. & .. & P_{2NG} \\ .. & . & P_{ij} & .. & .. \\ .. & .. & .. & .. & .. \\ P_{NP1} & P_{NP2} & .. & .. & P_{NPNG} \end{bmatrix} \qquad (3.3)$$

Where P_{ij} is the i_{th} position component of particle j and it represents the real power generation of generator i of the possible solution j.

➢ Initialization of the swarm

Each particle of the swarm matrix is initialized randomly within the real power operating limits using equation:

$$P_i^{min} \leq P_{ij} \leq P_i^{max} \qquad (j = 1,2, \ldots.., NP; \;\; i = 1,2, \ldots, NG) \qquad (3.4)$$

The velocities of the particles are initialized randomly according to the following inequality:

$$V_i^{min} \leq V_{ij} \leq V_i^{max} \qquad (j = 1,2, \ldots.., NP; \;\; i = 1,2, \ldots, NG) \qquad (3.5)$$

This velocity-initialization scheme always guarantees to produce new particles satisfying real power operating limit constraints. The maximum velocity limit in the i_{th} dimension is computed as:

$$V_i^{max} = \frac{P_i^{max} - P_i^{min}}{\alpha} \qquad (3.6)$$

$$V_i^{min} = -V_i^{max} \qquad (3.7)$$

Where α is the chosen number of intervals in the i_{th} dimension.

- **Evaluation of objective function**

Objective function is evaluated subjected to equality and inequality constraints.

- **Initialization of the best positions**

In the strategy of PSO, the particle's best position, P_{ij}^{best} and global best position G_i^{best} are the key factors. The position of the particle with minimum value of objective function value is the particle's best position. The best position out of all the P_{ij}^{best} is taken as G_i^{best}.

- **Movement of the particles**

The particles in the swarm are accelerated towards new positions by adding new velocities to their present positions. The new velocities are calculated using Eq. (3.1) and the positions of the particles are updated using Eq. (3.2).

$$V_{ij}^{new} = w \times V_{ij} + C_1 \times rand() \times \left(P_{ij}^{best} - P_{ij}\right) + C_2 \times rand() \times \left(G_i^{best} - P_{ij}\right) \qquad (3.8)$$

$$P_{ij}^{new} = P_{ij} + V_{ij}^{new} \qquad (j = 1,2, \ldots., NP;\ \ i = 1,2, \ldots, NG) \qquad (3.9)$$

If any position P_{ij} violates the real power operating limit constraints, it is clamped at the boundary value using equation

- **Updating the best positions**

The particles are evaluated for the new positions. Then P_{ij}^{best} of the particles are updated. The best position out of all the new P_{ij}^{best} is taken as G_i^{best}. An objective value at G_i^{best} is saved as f_{best}.

- **Stopping criterion**

Stochastic optimization algorithm can be stopped by various available critereon. Some examples of the available such criterion are tolerance, number of function evaluations and the maximum number of iterations. In this section, the maximum number of iterations is chosen as the stopping criterion. G_i^{best} is the optimum generation schedule and f_{best} is the minimum generation cost of the economic dispatch problem.

3.5 ADVANTAGES AND DISADVANTAGES OF PSO

A PSO is considered as one of the most powerful methods for resolving the non-smooth global optimization problems and has many advantages as compared to other heuristic optimization techniques, which are as follow:

- PSO is a derivative-free technique just like as other heuristic optimization techniques.
- PSO is easy in its concept and coding implementation.
- PSO is less sensitivity to the nature of the objective function compared to the conventional mathematical approaches and other heuristic methods.
- PSO has limited number of parameters including only inertia weight factor and two acceleration coefficients [49].
- PSO seems to be somewhat less dependent of a set of initial points compared to other evolutionary methods, implying that convergence algorithm is robust.
- PSO techniques can generate high-quality solutions within shorter calculation time and stable convergence characteristics [50].

The major *drawback* of PSO, like in other heuristic optimization techniques, is that it lacks a solid mathematical foundation for analysis to be overcome in the future development of relevant theories. Also, it can have some limitations for real-time ED applications such as 5-minute dispatch considering network constraints since the PSO is also a variant of stochastic optimization techniques requires relatively a longer computation time than mathematical approaches. It has the problems of dependency on initial point and parameters, difficulty in finding their optimal design parameters, and the stochastic characteristic of the final outputs [51].

CHAPTER 4

STOCHASTIC ECONOMIC-EMISSION LOAD DISPATCH USING PSO

The economic-emission load dispatch (EELD) problem is a multiple non-commensurable objective problem that minimizes both cost and emission together. Solution approach to this problem is given as follow:

4.1 SOLUTION APPROACH

To generate the non-inferior solution of multi-objective optimization problem, the weighting method is used. In this method the problem is converted into a scalar optimization as

Minimize

$$Fit = (w_1\bar{F}_1 + w_2\bar{F}_2 + w_3\bar{F}_3) \tag{4.1}$$

Where $\bar{F}_1, \bar{F}_2 and \bar{F}_3$ are the three objective functions as given in equations (2.8), (2.11) & (2.14).

Subject to

$$\sum_{i=1}^{NG} \bar{P}_i = \bar{P}_D + \bar{P}_L \tag{4.2}$$

$$\bar{P}_i^{min} \le \bar{P}_i \le \bar{P}_i^{max} \qquad (i = 1,2,\dots,NG) \tag{4.3}$$

$$\sum_{k=1}^{3} \mathrm{w_k} = 1, \mathrm{w_k} \ge 0 \tag{4.4}$$

Where $\mathrm{w_k}$ are the levels of the weighting coefficients. This approach yields meaningful results when solved for different scalar weight combinations $\mathrm{w_k}$ where k=1,2,3. The values of weighing coefficients vary from 0 to 1.

This weighting method is used in PSO optimization technique to obtain minimum and maximum values of objective functions. In order to satisfy the power balance constraint error is calculated using the equation:

$$error = \sum_{i=1}^{NG} \bar{P}_i - loss - demand \tag{4.5}$$

This error is now introduced in objective function equation to penalize the fitness function and the equation (4.1) becomes

$$f = Fit + r \times error^2 \tag{4.6}$$

Where 'r' is a number with large value.

4.1.1 Algorithm to search minimum and maximum values of objective functions

1. Read data: viz. cost coefficients i.e. $a_i,\ b_i, and\ c_i$, emission coefficients i.e. $d_i,\ e_i, and\ f_i$, minimum and maximum value of generation i.e. P_i^{max} & P_i^{min}, number of units i.e. i, maximum allowed iterations i.e. k, load demand, loss-coefficients, coefficient of variation, correlation coefficient etc.
2. Generate population (Power) i.e. P and velocity i.e. V randomly within limits.
3. Calculate LOSS using equation (2.17)
4. Calculate ERROR for each population using equation (4.5)
5. Calculate FITNESS for all population using equation (4.6).
6. LOCAL BEST VALUE: Initialize local best fitness as $Lfit = Fit$ and local best position as $Lbest = P$
7. GLOBAL BEST VALUE: The best value among the local best values i.e. the value with the minimum fitness is selected as global best fitness and the corresponding positions are considered as global best positions.
8. Set iteration counter to zero.
9. NEW VELOCITY is calculated for each population using equation (3.1) and is checked if it lies within the assigned maximum and minimum limits. If the given velocity is less than the minimum value then it is made equal to that value and if it is greater than the maximum value then it is made equal to that value.

10. Positions are updated using equation (3.2) and are checked if they lie within the maximum and minimum limits and are updated accordingly.
11. Loss is calculated for updated positions.
12. Error is calculated for updated loss and positions.
13. NEW FITNESS is calculated for updated positions using equation(4.6)
14. NEW LOCAL BEST VALUES: If the evaluated fitness of the given population is better than the previous fitness then the local best fitness is set to this fitness otherwise to previous fitness and the local best positions are updated accordingly, corresponding to the local best fitness.
15. NEW GLOBAL BEST VALUE: The best value among the local best values i.e. the value with the minimum fitness is selected as global best fitness and the corresponding positions are considered as global best positions.
16. Next iteration starts and the process is continued till the maximum iteration is reached.
17. This complete process is repeated for different values of weights i.e. $w1, w2\ and\ w3$.
18. From the set of the results obtained for different values of weights, we select minimum and maximum values of the three objective functions i.e. $F_1^{min}, F_1^{max}, F_2^{min}, F_2^{max}, F_3^{min}, F_3^{max}$.

4.2 DECISION MAKING

Due to the imprecise nature of the judgment, there may be fuzzy or imprecise goals for each objective function. The fuzzy sets are defined by equations called membership functions. These functions represent the degree of membership in certain fuzzy sets using values from 0 to 1 [42]. The membership value 0 indicates incompatibility with the sets, while 1 denotes full compatibility. By taking into account the minimum and maximum values of each objective function together with the rate of increase of membership satisfaction, membership function $\mu(\bar{F}_o)$ can be determined in a subjective manner. Here it is assumed that $\mu(\bar{F}_o)$ is a strictly monotonic decreasing and continuous, function defined as

$$\mu(\bar{F}_o) = \begin{cases} 1 & ; \bar{F}_0 \leq \bar{F}_o^{min} \\ \frac{\bar{F}_o^{max} - \bar{F}_o}{\bar{F}_o^{max} - \bar{F}_o^{min}} & ; \bar{F}_o^{min} < \bar{F}_o < \bar{F}_o^{max} \\ 0 & ; \bar{F}_o \geq \bar{F}_o^{max} \end{cases} \tag{4.7}$$

The value of membership function for different objectives '$\mu(\bar{F}_o)$' indicates how much (in the scale of 0 to 1) a non-inferior (non-dominated) solution has satisfied the $\bar{F}_o$ objective.

Constraints are handled as another objective function given by

$$\mu_4 = \frac{\alpha}{1 + error^2} \tag{4.8}$$

Where α is a small value.

The maximum satisfaction of membership function for any weight combination is obtained by taking intersection of the membership functions of participating objectives and is given below.

$$\mu_D = Min[\mu(\bar{F}_1), \mu(\bar{F}_2), \mu(\bar{F}_3), \mu_4] \tag{4.9}$$

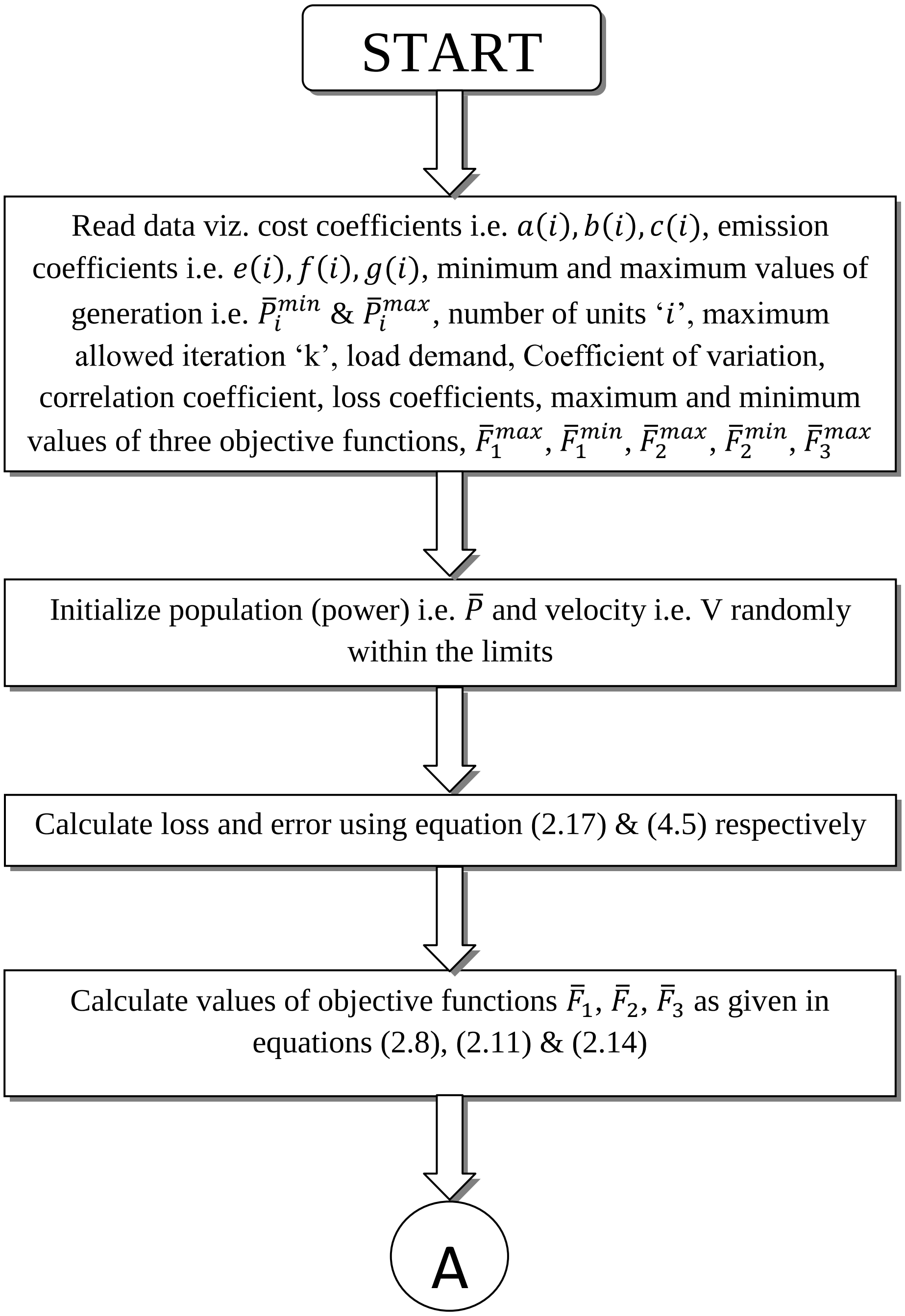
PSO search is used to obtain the best optimal solution. The function μ_D in Eq. (4.9) can be treated as a membership function for non-dominated solutions in a fuzzy set and represented as fuzzy cardinal priority ranking of the non-dominated solutions. The solution that attains the maximum membership μ_D in the fuzzy set so obtained can be chosen as the best solution or that having the highest cardinal priority ranking.

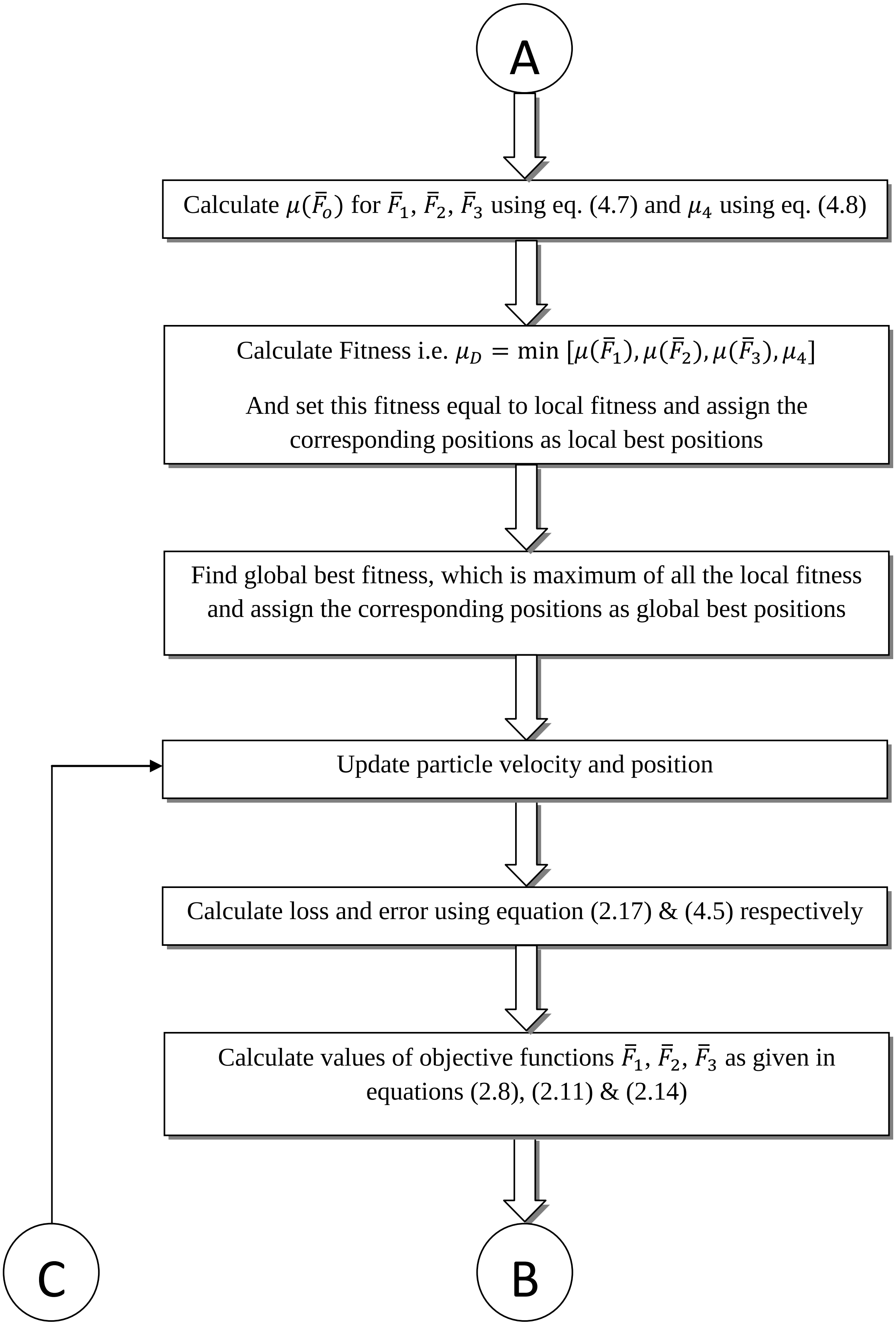
$$\text{Best optimal solution} = \text{Max } \{\mu_D\} \tag{4.10}$$

4.2.1 Flowchart to obtain the best optimal solution

Various steps used in finding the best optimal solution and its corresponding positions are shown in flowchart in fig. 4.1 and is summarized as follow:

First Population (power) and velocity are initialized randomly within range. After that Loss and error are calculated, which are further used to calculate objective functions$\bar{F}_1$, $\bar{F}_2$ & $\bar{F}_3$. Membership functions $\mu(\bar{F}_1), \mu(\bar{F}_2), \mu(\bar{F}_3)$ & μ_4 are calculated, then fitness is calculated using eq. (4.9) which is made equal to local fitness and then global fitness is found using eq. (4.10). Then new velocity is calculated and positions are updated. Corresponding to the updated positions loss and error are calculated, which are used to evaluate objective functions $\bar{F}_1$, $\bar{F}_2$ & $\bar{F}_3$ and then membership functions $\mu(\bar{F}_1), \mu(\bar{F}_2), \mu(\bar{F}_3)$ & μ_4 are calculated. Fitness is calculated using equation (4.9), if it is greater than local fitness then set this fitness as local fitness and maximum of all the fitness is set as global fitness. This process is repeated until maximum iterations are reached.




A
Calculate $\mu(\bar{F}_o)$ for $\bar{F}_1$, $\bar{F}_2$, $\bar{F}_3$ using eq. (4.7) and μ_4 using eq. (4.8)
Calculate Fitness i.e. $\mu_D = \min\,[\mu(\bar{F}_1), \mu(\bar{F}_2), \mu(\bar{F}_3), \mu_4]$
And set this fitness equal to local fitness and assign the corresponding positions as local best positions
Find global best fitness, which is maximum of all the local fitness and assign the corresponding positions as global best positions
Update particle velocity and position
Calculate loss and error using equation (2.17) & (4.5) respectively
Calculate values of objective functions $\bar{F}_1$, $\bar{F}_2$, $\bar{F}_3$ as given in equations (2.8), (2.11) & (2.14)
C
B

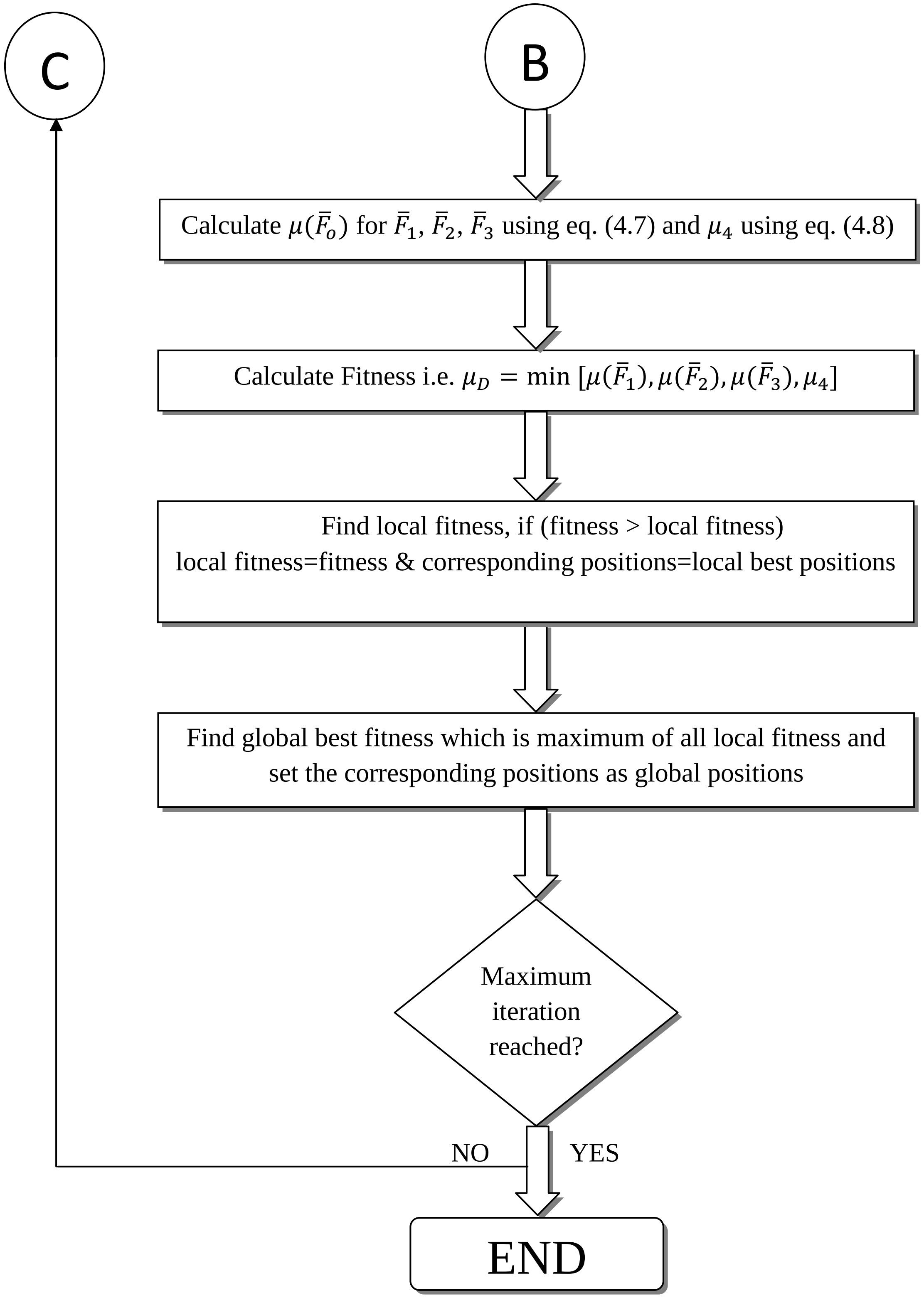


Fig. 4.1 Flowchart to obtain best optimal solutions

CHAPTER 5

RESULTS AND DISCUSSIONS

The developed algorithm in chapter 4 is applied to six-generator sample system in order to demonstrate its applicability. Expected generator characteristics are given in Table A of Appendix. Expected B-coefficients of transmission loss formula are presented in Table B of Appendix. In addition, following values of coefficient of variation (CV) for different values of random variables are assumed:

$$C_{a_i} = 0.1, C_{b_i} = 0.1, C_{d_i} = 0, C_{e_i} = 0, C_{P_i} = 0.1 \qquad (i = 1,2, \dots ,6)$$

As the case considered here is case with independent variables, therefore the values assumed for correlation coefficient (CC) for different random variables are zero i.e.

$$R_{a_iP_i} = R_{b_iP_i} = R_{d_iP_i} = R_{e_iP_i} = R_{P_iP_j} = 0.0 \qquad (i = 1,2, \dots ,6;\; j = 1,2, \dots ,6)$$

Three cases are considered for three different load demands.

- **Calculation of Minimum and Maximum values of objectives**

Minimum values of the objectives are obtained by giving full weightage to one of the objectives and neglecting the others. When the given weight value is 1.0, it means full weightage is given to the objective and when the weightage is zero the objective is neglected. Maximum objective values are obtained by exploiting their conflicting nature. The conflicting nature of the objectives, $\bar{F}_2$ and $\bar{F}_3$, will have maximum values when $\bar{F}_1$ is minimum.

The non-inferior solutions for 30 different simulated weight combinations are generated considering all the objectives simultaneously. To simulate weight combinations, weights are varied from 0 to 1.0 in steps of 0.1 so that their sum is 1.0.

- **Calculation of the best optimal solution and the corresponding expected optimal generation schedule**

After calculating minimum and maximum values of different objective functions, membership function is calculated for all the objective functions. Here constraints are handled as another objective, therefore membership function is also calculated for this objective as given in equation (4.8), in addition to the objective functions associated with economic dispatch, emission dispatch and expected deviations as given in equation (2.8), (2.11) & (2.14). So these non-inferior solutions can be treated as a fuzzy set. PSO is used to search the highest cardinal priority ranking, which is chosen as the best solution.

5.1 CASE1: When demand is 500MW

The algorithm developed in previous chapter is applied to get the maximum and minimum values of the three objectives, which are given below in Table 1.

TABLE 1. Maximum and Minimum values of objective functions for demand 500MW

Objective function	Maximum value	Minimum value
$\overline{F}_1$ (Rs./hr)	31954.67	28348.46
$\overline{F}_2$ (Kg/hr)	990.6199	711.7856
$\overline{F}_3$ (MW^2)	1013.425	544.5984

After calculating the minimum and maximum values of objective functions, membership function $\mu(\overline{F}_1), \mu(\overline{F}_2), \mu(\overline{F}_3), \mu_4$ is calculated for all the population and then μ_D is calculated using equation (4.9). PSO is used to find the solution with highest cardinal ranking and that solution is selected as best compromised solution as indicated in table 2. The values of expected power corresponding to the best optimal solution are given in table 3.

TABLE 2. Best optimal solutions for demand 500MW

Demand (MW)	$\overline{F}_1$ (Rs./hr)	$\overline{F}_2$ (Kg/hr)	$\overline{F}_3$ (MW^2)
500	28463.82	720.7172	559.6096

Values obtained for different objective functions lie within their respective maximum and minimum values given in Table 1.

TABLE 3. Expected optimal generation schedules for demand 500MW

Demand (MW)	$\overline{P}_1$ (MW)	$\overline{P}_2$ (MW)	$\overline{P}_3$ (MW)	$\overline{P}_4$ (MW)	$\overline{P}_5$ (MW)	$\overline{P}_6$ (MW)	$\overline{P}_L$ (MW)
500	62.7904	44.22371	46.5143	78.79546	161.4475	125.0	18.95238

The values of expected powers obtained above lie within their respective maximum and minimum limits and thus satisfy the power balance constraint.

5.2 CASE2: When demand is 700MW

The minimum and maximum values of the three objectives obtained from different combinations of weights are given below in Table 4.

TABLE 4. Maximum and Minimum values of objective functions for demand 700MW

Objective function	Maximum value	Minimum value
$\overline{F}_1$ **(Rs./hr)**	41471.34	38664.35
$\overline{F}_2$ **(Kg/hr)**	1240.365	1049.427
$\overline{F}_3$ (MW^2)	1393.446	1020.17

The maximum and minimum values of objective functions obtained above are used to calculate membership function $\mu(\overline{F}_1), \mu(\overline{F}_2), \mu(\overline{F}_3), \mu_4$ and then μ_D is calculated for all population using equation (4.9). PSO is used to find the solution with highest cardinal ranking, which is selected as best compromised solution as shown in table 5. The values of power corresponding to the best optimal solution are shown in table 6.

TABLE 5. Best optimal solutions for demand 700MW

Demand (MW)	$\overline{F}_1$ (Rs./hr)	$\overline{F}_2$ (Kg/hr)	$\overline{F}_3$ (MW^2)
700	39163.8	1083.413	1086.624

Expected values of objective functions thus obtained lie within their respective maximum and minimum values as given in Table 4.

TABLE 6. Expected optimal generation schedules for demand 700MW

Demand (MW)	$\overline{P}_1$ (MW)	$\overline{P}_2$ (MW)	$\overline{P}_3$ (MW)	$\overline{P}_4$ (MW)	$\overline{P}_5$ (MW)	$\overline{P}_6$ (MW)	$\overline{P}_L$ (MW)
700	97.85734	71.66454	64.89748	113.1621	219.798	169.1803	37.02

The values of expected powers obtained above lie within their respective maximum and minimum limits and thus satisfy the power balance constraint.

5.3 CASE3: When demand is 900MW

The minimum and maximum values of the three objectives obtained from different combinations of weights are given below in Table 7.

TABLE 7. Maximum and Minimum values of objective functions for demand 900MW

Objective function	Maximum value	Minimum value
$\overline{F}_1$ (Rs./hr)	58290.09	50118.85
$\overline{F}_2$ (Kg/hr)	9693.177	1577.799
$\overline{F}_3$ (MW^2)	10102.28	1821.751

After calculating the minimum and maximum values of objective functions, membership function $\mu(\bar{F}_1), \mu(\bar{F}_2), \mu(\bar{F}_3), \mu_4$ is calculated for all the population and then μ_D is calculated using equation (4.9). PSO is used to find the solution with highest cardinal ranking, which is selected as best compromised solution as indicated in Table 8. Values of power corresponding to best optimal solution are shown in Table 9.

TABLE 8. Best optimal solutions for demand 900MW

Demand (MW)	$\overline{F}_1$ (Rs./hr)	$\overline{F}_2$ (Kg/hr)	$\overline{F}_3$ (MW^2)
900	50282.8	1636.951	1987.925

Expected values obtained in Table 8 for different objective functions lie within their respective maximum and minimum values given in Table 7.

TABLE 9. Expected optimal generation schedules for demand 900MW

Demand (MW)	$\overline{P}_1$ (MW)	$\overline{P}_2$ (MW)	$\overline{P}_3$ (MW)	$\overline{P}_4$ (MW)	$\overline{P}_5$ (MW)	$\overline{P}_6$ (MW)	$\overline{P}_L$ (MW)
900	112.1715	82.907050	75.190620	147.73620	314.28850	230.3900	62.82637

5.4 COMPARISON OF RESULTS

Here the results obtained above are compared with the earlier work carried out and the results obtained by DP Kothari and JS Dhillon [33]

5.4.1 CASE1: When demand is 500MW

The expected values of different objectives and loss obtained from PSO in Table 2 are compared with the results mentioned in reference [33]. From Table 10 it can be concluded that there is 0.045% decrease in operating cost and 0.712% decrease in emissions, with a slight increase of 0.152% in deviations associated with unsatisfied load demand. Here losses are also decreased by 9.743%.

TABLE 10. Comparison of Best optimal solutions for demand 500MW

Test System	Demand(MW)	$\overline{F}_1$ (Rs./hr)	$\overline{F}_2$ (Kg/hr)	$\overline{F}_3$ (MW^2)	$\overline{P}_L$ (MW)
PSO	500	28463.82	720.7172	559.6096	18.95238
NR [33]	500	28476.63	725.852	558.758	20.799

5.4.2 CASE2: When demand is 700MW

When the results obtained from PSO are compared with the results mentioned in reference [33], showed that emissions are decreased by 1.982 % and deviations are decreased by 2.545% but at the expense of economy which is increased by 0.39%. Expected losses are also decreased by 7.15%.

TABLE 11. Comparison of Best optimal solutions for demand 700MW

Test System	Demand(MW)	$\bar{F}_1$ (Rs./hr)	$\bar{F}_2$ (Kg/hr)	$\bar{F}_3$ (MW^2)	$\bar{P}_L$ (MW)
PSO	700	39163.8	1083.413	1086.624	37.02
NR [33]	700	39010.74	1104.897	1114.285	39.669

5.4.3 CASE3: When demand is 900MW

When the results obtained from PSO are compared with the results mentioned in reference [33], showed that operating cost is decreased by 1.137% but at the expense of emissions and deviations, which increased by 3.403% and 6.38% respectively. But losses decreased by 3.51%.

TABLE 12. Comparison of Best optimal solutions for demand 900MW

Test System	Demand (MW)	$\bar{F}_1$ (Rs./hr)	$\bar{F}_2$ (Kg/hr)	$\bar{F}_3$ (MW^2)	$\bar{P}_L$ (MW)
PSO	900	**50282.8**	**1636.951**	**1987.925**	**62.82637**
NR [33]	900	50854.86	1581.243	1861.073	65.032

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

The public attitude towards environmental issues necessitates the optimal economic-environmental power dispatch. In the traditional power dispatch problems, all the variables involved are treated as deterministic ones and the inaccuracies and uncertainties inherent in the practical power system operations are ignored. In this thesis, the EED problem is formulated as a stochastic one, where multiple objectives need to be minimized simultaneously while satisfying the imposed constraints such as generating capacities and power flow balance. Weighting method is used to obtain minimum and maximum values of objective functions. Membership function is calculated for all the objective functions and also for the constraints which are handled as another objective. PSO is used for finding the highest cardinal priority ranking of the intersection of the membership functions of the fuzzy sets. The PSO algorithm approach yields solutions which are optimal or near optimal. The results obtained for the six unit system showed that the PSO algorithm was good in terms of its potential in solving ED problems and also computational cost and convergence stability besides the high quality of solutions.

6.2 SCOPE OF FUTURE WORK

The proposed approach can be applied to a large-scale practical system, which has nonlinear and rigid constraints.

Practically there are many pollutants like oxides of carbon, oxides of sulphur, oxides of nitrogen, so the number of objective functions can increase and the problem can be solved considering all the pollutants.

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APPENDIX

Table A

Six unit generator characteristics

Generator No.	$\overline{P_j^{min}}$	$\overline{P_j^{max}}$	$\overline{a_j}$	$\overline{b_j}$	$\overline{c_j}$	$\overline{d_j}$	$\overline{e_j}$	$\overline{f_j}$
1	10	125	0.15247	38.53973	756.79886	0.00419	0.32767	13.85932
2	10	150	0.10587	46.15916	451.32513	0.00419	0.32767	13.85932
3	35	225	0.02803	40.39655	1049.99770	0.00683	0.54551	40.2669
4	35	210	0.03546	38.30553	1243.53110	0.00683	0.54551	40.2669
5	130	325	0.02111	36.32782	1658.56960	0.00461	0.51116	42.89553
6	125	315	0.01799	38.27041	1356.65920	0.00461	0.51116	42.89553

Table B

Expected loss coefficients

0.002022	-0.000286	-0.000533	-0.000565	-0.000454	0.000103
-0.000286	0.003243	0.000016	-0.000307	-0.000422	-0.000147
-0.000533	0.000016	0.002085	0.000831	0.000023	-0.000270
-0.000565	-0.000307	0.000831	0.001129	0.000113	-0.000295
-0.000454	-0.000422	0.000023	0.000113	0.000460	-0.000153
0.000103	-0.000147	-0.000270	-0.000295	-0.000153	0.000898