MULTIOBJECTIVE ECONOMIC LOAD DISPATCH USING PARTICLE SWARM OPTIMIZATION

A Thesis submitted in partial fulfillment of the requirements for the award of degree of

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CERTIFICATE

I hereby certify that the work which is being presented in this Thesis entitled, **"Multi Objective Economic Load Dispatch Using Particle Swarm Optimization"**, in partial fulfillment of the requirements for the award of degree of **Master of Engineering in Power Systems and Electric Drives at Thapar University**, Patiala, is an authentic record of my own work carried out under the supervision of **Mr. Nitin Narang, Assistant Professor (EIED)**. The matter embodied in this Thesis has not been submitted for the award of any other degree to any other university.

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

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ABSTRACT

A major objective for the Thermal power generation is to minimize fuel consumption by allocating optimal power generation to each unit (Economic Dispatch) and to maintain emissions within the environmental license limit (Emission Dispatch) subject to equality and inequality constraints. Due to conflicting nature of emission and economy objectives, problem becomes multiobjective in nature.

In this research work weighting method is applied to convert multiobjective optimization problem in to scalar optimization. The weighting method assigns different weights to each objective function based on its importance. The Particle Swarm Optimization (PSO) technique is applied to find the best comprised solution. The thermal unit is selected as decision variable and it is searched within defined search area. The equality constraint is handled by exterior penalty method. Fuzzy cardinal approach is used to achieve the one best solution.

In order to show the effectiveness of this technique, the proposed approach is applied to three test systems. Numerical results obtained from this approach are compared with different techniques (differential evolution(DE), classical evolutionary programming(CEP), fast evolutionary programming(FEP), mean(FEP) and improved (FEP),multi objective differential evolution (MODE) , pareto differential evolution (PDE), non dominated sorting genetic algorithm-II (NSGA-II) and strength pareto evolutionary algorithm 2 (SPEA 2) and are found satisfactory.

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CHAPTER 1. INTRODUCTION

1.1 Overview

Scheduling of power plant generation is of great importance for electric utility systems. One of the prime concerns from social and environment aspects is that both human and non-human life forms are severely affected by the atmospheric pollution caused during generation of electricity from fossil fuels. This may give rise to the problem of global warming. Due to increasing concern over the environmental consideration **[1],** society demands adequate and secure electricity not only at the cheapest possible price, but also at minimum level of pollution. So the optimal scheduling of generation in a thermal power plant system involves the allocation of generation so as to optimize the fuel cost and emission level simultaneously.

The remote location of power plant from the load centre has been identified as one of the reasons which caused high cost. The increase in fuel cost these days has also contributed to this phenomenon. Therefore, economic load dispatch is implemented in order to determine the output (generating) of each generator so that the total generation cost will be minimized. The generator's output has to be varied within limits so as to meet a particular load demand and losses with minimum fuel cost **[2].** Thus, Economic load dispatch (ELD) is one of the important topics to be considered in power system engineering. In addition, the increasing public awareness of the environmental protection and passage of clean Air Act Amendments of 1990 have forced the utilities to modify their design or operational strategies to reduce pollution and atmospheric emission of thermal plants. Apart from heat, power utilities using fossil fuel as primary energy source, produces harmful gasses such as CO_2, SO_2 and NO_x, which cause detrimental effect on human beings.

The solution of economic power dispatch or minimum emission problems, when attempted in isolation will be different and conflicting with each other therefore in order to solve these two objectives (economic and emission) simultaneously, the problem is formulated in to multiobjective problem. Thus multiobjective optimization problem minimize these competing objective functions while satisfying equality and inequality power constraints. The equality constraints are the power balance constraint .The inequality constraints are due to the generation limits of thermal power plant.

Multiobjective problem is converted in to scalar optimization with the help of weighting method. This approach yields meaningful results to the decision makers only when solved many times for different values of weights. **[3]**

In this thesis work one of most recent heuristic technique Particle swarm optimization (PSO) is used. This technique is based on the experience gained from the study of artificial life and psychological research. Eberhart and Kennedy developed PSO, based on the analogy of the swarm of birds and the school of fish [**3**]. One of the main goals is to examine how natural creatures behave as a swarm and to reconfigure the swarm model computationally. It is well known that the PSO techniques can provide a high-quality solution with simple implementation and fast convergence [**4**]–[**9**]. PSO algorithm has been developed for the nonlinear continuous optimization problem to achieve the best compromise solution.

1.2 Literature Review

Despite extensive research focusing on thermal economic dispatch, emission dispatch and mutiobjective problem, much of the efforts still today have involved so as to obtain the most optimal dispatch at most optimal cost.

Happ [10] and an **IEEE Working Group [11,12]** present the work of authors from the inception of economy loading to the status existing in 1979. Happ reviews the progress of optimal dispatch going as far back as the early 1920's, 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 were in use such as: (a) 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., (b) "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, etc. It was recognized as early as 1930, that the incremental method, later known as the equal incremental method, yielded the most economic results.

Generation dispatch has been widely studied and reported by several authors in books on power system analysis [**13-18].** Some authors present various aspects of optimal power flow while others present the development of interfaces between such control actions such as economic dispatch (ED) and load frequency control (LFC). Economic dispatch and load frequency control both have the task of adjusting the area generation such that it matches the area load while, simultaneously, both area frequency and the net tie-line exchange are at their set points

Carpentier [19] chronicles the development of optimal power flows from its inception in 1961 and goes on to review several solution methods in existence in 1978. A review of the optimal power flow (OPF) methods is also provided by **Talukdar, *et al.* [20]** and **Burchett, *et al.* [21]**. The authors in both of these references discuss the relative performance criteria for different methodologies being employed in these procedures

Luo, *et al.* [22] reduce the economic dispatch problem to a concise set of quasi-linear equations resulting in a solution form similar to that of an electric network. The equations are in terms of the bus incremental cost, otherwise known as the Lagrange multipliers. **Luo, *et al*. [23]** using ideas from their previous paper **[22]** develop a network model for the economic dispatch problem using the bus incremental costs as potential quantities. According to the authors' theory, an area system may be reduced to a Thevenin equivalent for economic dispatching by means of the network model.

Shoults, *et al.* [24] present an alternative approach for computation of loss coefficients, or more popularly known as B-Constants. The authors have used the method of least squares to this end and have demonstrated the simplicity and computational advantages over methods based on the earlier Kron's method.. The authors incorporate this method of computing loss coefficients in a classical economic dispatch and demonstrate its computational advantage over a dispatch method using load flow techniques.

El-Hawary, *et al.* [25] study the relative performance of four algorithms used for parameter estimation in models used for optimal power flow. The models are 1) weighted least squares, 2) Gauss-Newton method or Bard algorithm, 3) Marquardt algorithm, and 4) Powell regression algorithm. The authors found an overall better performance by the weighted least squares method. In another paper of a similar nature, **El-Hawary, *et al.* [26]** compare the performance of a hybrid method of Powell and the Newton-Raphson method. Faster solution of the coordination equations are achieved by the former method thus making its convergence characteristics superior.

Several approaches have been discussed to overcome the drawbacks of classical economic load dispatch ELD problem. Some of these methods have been based on successive linear programming and successive quadratic programming described by different authors in literature. Different methods for power System operation has been discussed by **Miller and Malinnowski [2].**

According to **Palanichamy and Shrikrishna[27]** discussed Simple algorithm for economic power dispatch for optimizing the problem while satisfying a set of system operating constraints, including constraints dictated by the electric network. ELD has been widely used in power system operation and planning discussed by **Wood and Woolenberg [17].**

In previous research, different approaches have been suggested, including linear programming and nonlinear programming **[28]–[30]**. Linear programming methods are fast and reliable, but the main drawback is that they are associated with the piecewise linear cost approximation **[28]**. The nonlinear programming approaches have a problem of algorithm convergence and complexity **[30]**.

Different heuristic approaches have been proved to be effective with promising performance, such as evolutionary programming (EP) **[31]–[33]**, simulated annealing (SA) **[34]**, tabu search (TS) **[35]**, pattern search (PS) **[36]**, genetic algorithm (GA) **[37]**, differential evolution (DE) **[38]**, and particle swarm optimization (PSO) **[39]**. Although the heuristic methods do not always guarantee discovering globally optimal solutions in finite time, they often provide a fast and reasonable solution.

Meng, *et al.* [40], proposed a heuristic optimization method, Quantum-inspired Particle Swarm Optimization (QPSO) to solve valve-point Economic load dispatch problem. It has stronger search ability and quicker convergence speed, not only because of the introduction of quantum computing theory, but also due to two special implementations: self-adaptive probability selection and chaotic sequences mutation.

Amjady and Sharifzaden [41] present a modified differential evolution (MDE) algorithm method to solve economic load dispatch (ELD) problem considering valve point loading. Considering valve loading effect changes ELD into a non-convex optimization problem. This non-convexity challenges analytical and heuristic methods in finding optimal solution in reasonable time. MDE is in the framework of differential evolution owning new mutation operator and selection mechanism inspired from Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA), respectively. In other words, positive characteristics of DE, GA, PSO and SA are combined to create a new efficient stochastic search technique.

Alsumait, *et al.* [42] proposed a approach based on a hybrid algorithm consisting of Genetic Algorithm (GA), Pattern Search (PS) and Sequential Quadratic Programming (SQP) techniques to solve the well-known power system Economic dispatch problem (ED). GA is the main optimizer of the algorithm, whereas PS and SQP are used to fine tune the results of GA to increase confidence in the solution

Kothari, ***et al***. [**43**] exhibited a computer oriented technique for thermal power generation scheduling which resulted in minimum NO_x emission. Optimal fuel mix and load dispatching under environmental constraints is the operation of a generation system so that power plant with higher emission rates generate less than they would under least cost dispatching was hinted by **Tsuji**[**44**].

Dhillon, *et al.* [45] proposed a novel binary successive approximation-based evolutionary search strategy to solve economic-emission dispatch. This technique has emerged as useful optimization tool for handling network losses, ramp rate limits, valve point loading and prohibited zone avoidance into account to determine the goal optimal dispatch solution as well as operating point in the non-inferior domain for any number of goals. This technique has proved efficient for minimising the emission level.

Nanda, ***et al***. [**46**] suggested a computational approach employing an improved complex box method to find minimum emission dispatch. In another attempt **Nanda, *et al***. [**47**] expressed a goal programming technique to solve the economic load dispatch problem for thermal generating unit running with natural gas and fuel oil.

Brodsky and Hann [**48**] presented a model on assessing the influence of power pools on emission constrained economic dispatch, to show that emission and production cost were a function of the organizational form. They illustrated that the production cost and emission could be reduced with increased coordination among utilities.

Dhillon, ***et al.*** **[49]** formulated multiobjective stochastic optimal thermal power dispatch problem. They considered objectives such as operating cost, minimal emission and minimum transmission losses in thermal power dispatch systems, considering uncertainties and inaccuracies in system data.

Lily, ***et al.*** **[50]** has presented a multi-objective constraint handling method with the PSO algorithm for tackling power generation unit loading optimization problem. The proposed approach adopts the concept of dominance from multiobjective optimization, and uses a few selection rules to guide the search direction.

Heo, ***et al*****. [51**] has explained that improvements can be made to the basic PSO technique to solve the multiobjective optimization problem effectively. It has been demonstrated that the hybrid PSO technique improves the convergence and performs the best compared with other PSO techniques in fosil fuel power units (FFPU).

Yalcinoz and Koksoy [52] suggested an optimization technique based on progressive articulation of preference information to solve the multiobjective environmental economic dispatch. In this method problem was handled in an interactive way and does not need to know any global preference structure or some type of initial goals of the decision maker for the objectives.

Abido [53] used a niched Pareto genetic algorithm (NPGA) based approach to solve the multiobjective environmental/economic dispatch (EED) problem. The proposed NPGA based approach handles the problem as a multiobjective problem with competing and non-commensurable cost and emission objectives. The proposed approach has diversity-preserving mechanism to find widely different Pareto-optimal solution. The comparison with the classical methods demonstrates the superiority of the proposed approach and confirms its potential to solve the multiobjective EED problem.

Basu [54] presents a simulated annealing-based goal-attainment method to solve economic emission load dispatch of hydrothermal power system. In this method multiobjective problem was transformed into a single-objective optimization by the goal-attainment formulation. The disadvantage of this problem is the long execution time. This technique can be used as an effective technique for dealing with decision-making processes in presence of conflicting objectives.

Basu [55] proposed a multi-objective differential evolution [MODE] to solve Economic Emission dispatch (EED) problem. The problem is formulated as a non linear constrained multiobjective optimization problem. Results obtained from the proposed approach are comparable to those obtained from pareto differential evolution, non dominated sorting genetic algorithm-II (NSGAII) and strength pareto evolutionary algorithm2 (SPEA2).

Basu [56] implemented nondominated sorting genetic algorithm-II (NSGAII) to deal with economic environmental dispatch problem of thermal plants with non smooth fuel cost and emission level functions in coordination with fixed head hydro units. The problem is formulated as non linear constrained multiobjective optimization problem.

Wu, ***et al*****. [57]** applied multi-objective differential evolution (MODE) algorithm to solve environmental/economic power dispatch (EED) problem. The results of proposed technique was compared with other multi-objective evolutionary algorithms(MOEAs)techniques , which confirms its potential for solving other power systems multi-objective optimization problems.

Wang and Singh [58] implemented fuzzified multi-objective particle swarm optimization (FMOPSO) algorithm to solve economic and emission power dispatch issues. In this work, the basic particle swarm algorithm was used to tackle the multi-objective case. The effectiveness of the proposed approach was demonstrated by comparing its performance with other approaches including weighted aggregation (WA) and evolutionary multi-objective optimization algorithms.

Gong, ***et al.*** **[59]** used hybrid multi-objective optimization algorithm based on particle swarm optimization (PSO) and differential evolution (DE) to solve the highly constrained environmental/economic dispatch problem involving conflicting objectives. In this method PSO was degined as time variant acceleration coefficients to explore the entire search space, while a local version of DE was proposed to exploit the sub-space with sparse solutions.

Abido [60] implemented a novel multiobjective particle swarm optimization technique (MOPSO) to solve environmental/economic power dispatch optimization problem. The proposed approach extends the single objective PSO by proposing the new definitions of the local best and global beat individuals in multiobjective optimization problems..

Wang and Singh [61] proposed Multi area environmental/economic dispatch (MAEED) , which is then handled by an improved multiobjective particle swarm optimization (MOPSO) algorithm for searching out a set of Pareto-optimal solutions. The results were compared with other two optimization methods including weighted aggregation and multiobjective evolutionary algorithm and found satisfactory.

Airashidi and El-Hawary [62] presented a PSO technique for solving multiobjective optimization problems like environmental/economic power dispatch (EED). Results showed that PSO was successfully capable of capturing the shape of Pareto solution sets. This technique can be e xtended to handle more than two objectives. Computation time, simplicity, and its capabilities of handling a wide class of optimization problems are key advantages of this powerful heuristic technique.

Abido [63] used a strength Pareto evolutionary algorithm (SPEA) based approach to handle environmental/economic dispatch EED as a true mutiobjective optimization problem with competing and non commensurable objectives. The proposed approach does not impose any limitation on the number of objectives, so more objectives, such as stability and security, can also be considered.

Jeyakumar, *et al.* [64] describes a Multi-Objective Evolutionary Programming (MOEP) method to solve the combined economic emission dispatch (CEED) problem. Problem was converted into single objective optimization problem using weighted sum method.

Airashidi and El-Hawary [65] presented a PSO algorithm as an effective tool for solving constrained multiobjective optimization problems like Economic Emission Dispatch (EED). Results showed that PSO was successfully capable of capturing the shape of Pareto solution sets.

Osman, *et al.* [66] presented a Epsilon-Dominance based multiobjective genetic algorithm approach for economic emission load dispatch (EELD) optimization problem. Authors presented a optimization algorithm which is based on concept of co-evolution and repair algorithm for handling nonlinear constraints. The algorithm maintains a finite-sized archive of non-dominated solutions which gets iteratively updated in the presence of solutions based on the concept of Epsilon (Ɛ)-dominance.

Singh and Dhillon [67] converted a multiobjective economic-emission dispatch problem into a scalar problem. This scalar set optimization problem is then solved for many types of different set of weight pattern to generate non-inferior solution along with trade-off functions between the conflicting objectives. The optimal solution is calculated by considering real and reactive power losses, which are calculated by performing fast decupled load flow analysis.

1.3 Author's Contribution

The multi objective optimization of power dispatch problem has been carried out considering the combination of economic dispatch, emission dispatch. The objective functions for these are minimization of fuel cost and emission. Multiobjective problem has been converted into scalar optimization using the weighting method. The particle swarm optimization (PSO) algorithm has been implemented to solve multiobjective optimization problem. In order to show the effectiveness of technique, the proposed results are compared with different techniques.

1.4 Organization of Thesis

The work carried out has been summarized in six chapters. The Chapter 1 highlights the brief introduction, summary of work carried out by various researchers. Author's contribution and the outline of the thesis also discussed in this chapter. The Chapter 2 explains the multiobjective optimization generation scheduling .The chapter 3 describes particle swarm optimization technique used for problem evaluation. The Chapter 4 describes the solution approach to multiobjective economic dispatch problem using the particle swarm optimization algorithm. The chapter 5 details the results pertaining to various cases and the comparison of results obtained for various solutions. The conclusions and the scope of further work are detailed in Chapter 6.

CHAPTER 2. MULTIOBJECTIVE OPTIMIZATION GENERATION SCHEDULING

2.1 Introduction

Optimization process consists of three basic components: an objective function, variables, and constraints. The optimization process finds the value of the variables that minimize or maximize the objective function while satisfying the constraints. The problem relies on many variables and therefore various combinations of values of the variables have to be explored to obtain the optimism of the objective function [**68**]. Sometimes many confliction criteria such as cost, capacity performance and reliability are to be considered simultaneously. It is very difficult to decide which selection is most suitable for the criteria because the criteria will conflict with each other. This is also called a multi objective optimization problem (MOOP).

The power dispatch problem is a nonlinear programming problem and is used to determine optimal outputs of generators in a power system with objective to minimize the total production cost while the system is operating within its constraints limit. The power dispatch problem aims to minimize the total cost of power generation from thermal power plants at various stations while satisfying the loads and losses in power transmission system [**69**]. The objective is to distribute the total demand and total loss among units connected while simultaneously minimizing generation cost and satisfying power balance equation and other constraints.

The operation of thermal power plants depends on combustion of fossil fuels which produces NO_x, SO_2 and CO_2 emissions. These emissions have given rise to environmental concerns. Even the Clean air act [**70**] persuades the utilities to change their practices to meet the environmental emission norms. Thus, it becomes important to perform the emission dispatch or include the emission constraints into the power dispatch. A minimum emission dispatch is performed in the same way as power dispatch with the end goal being to reduce emissions instead of costs. The fuel cost objective function is replaced by an emissions objective function. The constraints are the same but the optimal solution will produce the lowest total emissions as opposed to the lowest total cost.

The economy and emission functions are conflicting in nature and they both have to be considered simultaneously to find optimal dispatch. The situation is formulated as a multiobjective optimization problem in which the main aim is to minimise not a single objective (economy or emission) but to minimise both the objectives (economy and emission) simultaneously.

2.2 Economic Load Dispatch

The objective of the economic dispatch problem (EDP) of electric power generation, whose characteristics are complex and highly nonlinear, is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all generating units and system equality and inequality constraints [**71**]

The majority of generators in extant systems are of three types-nuclear, hydro, and fossil (coal, oil or gases). Figure 2.1 shows a simple model of a fossil plant. The power output of fossil fuel plant is increased sequentially by opening a set of valves a the inlet to its steam turbine. The throttling loses in a valve are large when it is just opened and small when it is fully opened **[3]**.

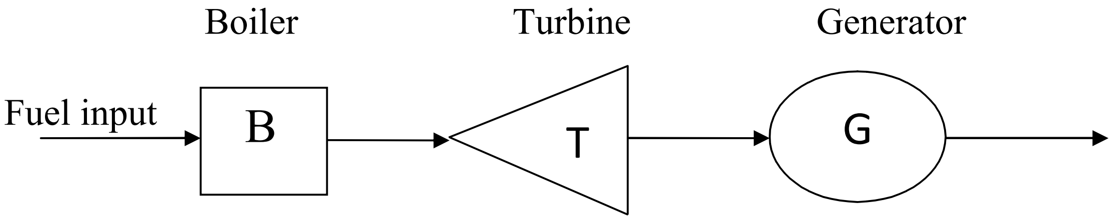

Fig: 2.1 Simple model of fossil fuel plant

As a result, the operating cost of the plant has the form shown in figure 2.2. For dispatching purposes, this cost is usually approximated by one or more quadratic segments. So, the fuel cost curve is modelled as a quadratic in the active power generation.**[3]**

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

Where a_i, b_i and c_i are the cost coefficients.

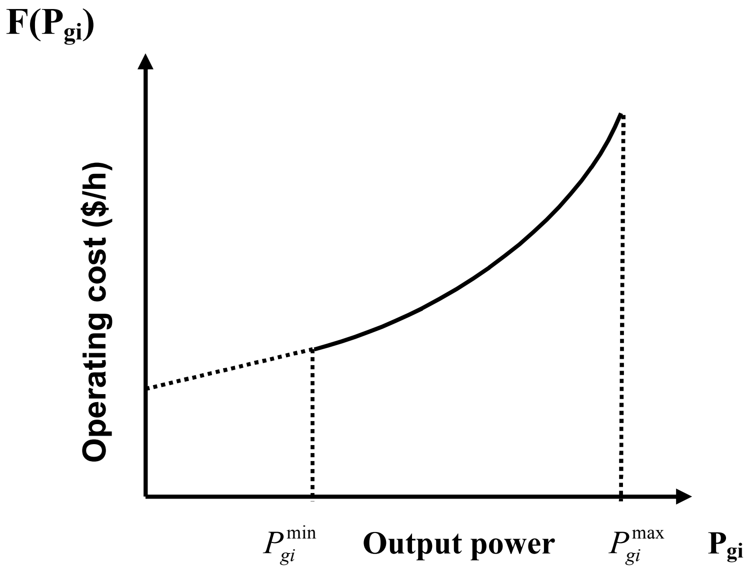

Fig: 2.2 Operating cost of a fossil-fired generator

The $P_{gi}^{\min}$ is the minimum loading limit below which it is uneconomical (or may be technically infeasible) to operate the unit and $P_{gi}^{\max}$ is the maximum output limit. The fuel cost curve may have a number of discontinuities. The discontinuities occur when the output power has to be extended by using additional boilers, steam condensers, or the other equipment. Discontinuities also appear if the cost represents the operation of entire power station, so that 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.

When the valve point effect is considered in the input output curve, the possibility of non-convex curves must be accounted for if extreme accuracy is desired. If non-convex input-output curves are to be used, equal incremental cost methodology cannot be used, since there are multiple outputs for any given value of incremental cost. Thereby the effects of valve-point loading is modelled as a recurring rectified sinusoid contribution and added to the basic quadratic cost function as in (2.1).[**3**]. Fig(2.3) shows the effect of valve point loading on Incremental cost.

The generating units with multi valve steam turbines exhibit a greater variation in the fuel cost functions, the valve point effects introduce ripples in the heat-rate curves. Mathematically the operating cost is defined as:

$$F\left(P_{\mathrm{gi}}\right)=\sum_{i=1}^{NG}\left(a_i\,P_{\mathrm{gi}}^2+b_i\,P_{\mathrm{gi}}+c_i+\left|e_i\sin\left(f_i\left(P_{i\min}-P_i\right)\right)\right|\right)\ \$/\mathrm{h} \tag{2.2}$$

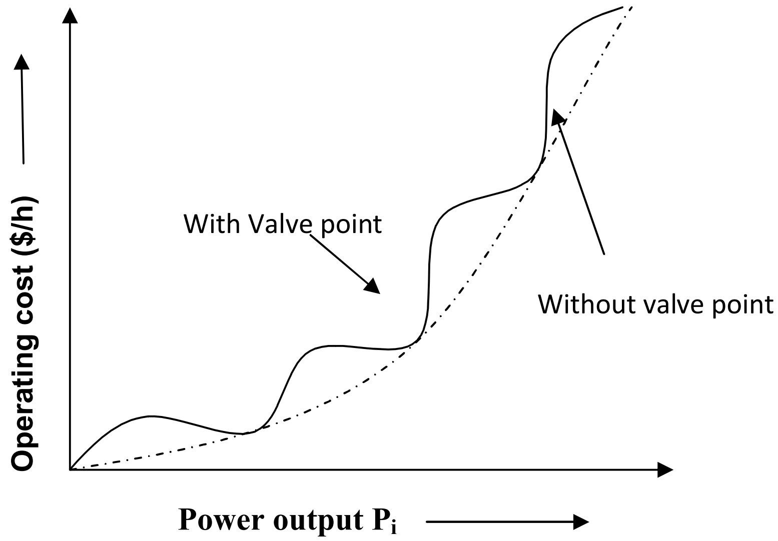

Fig 2.3: Incremental fuel cost with valve point loading

Where e_i and f_i are the fuel cost coefficients of unit i with valve-point effect. Now, the modified objective function for the ED problem is to minimize (2.2) subject to the constraints given in (2.7) and (2.9).

2.3 Emission Dispatch

The global warming is a concern for power industry, as it is accountable for the emission of green house gases in environment. As discussed earlier that amendment of clear air act and environmental friendly policies (Carbon Credit System) develops an interest of power sector towards reduction of emissions of NOx, SOx and CO_2 gases. Different mathematical formulations are used to represent the emission of green house gases in emission dispatch (EMD) problem. The emission dispatch function can be represented as:

$$F(P_{gi})=\sum_{i=1}^{NG}\left(\alpha_i P_{gi}^2+\beta_i P_{gi}+\gamma_i+\eta_i\exp(\delta_{\mathrm{i}} P_{gi})\right)\quad \text{ton/h} \tag{2.3}$$

where $\alpha_i,\beta_i,\gamma_i,\eta_i$ and δ_i are the emission coefficients.

The modified objective function for the EMD problem is to minimize (2.3) subject to the constraints given in (2.7) and (2.9).

2.4 Multiobjective Problem Formulation

The combined environmentally-economic dispatch (CEED) problem can be classified as a multiobjective optimization and nonlinear programming problem. The purpose of CEED is to estimate the optimal amount of the generated power by minimising the both objectives, fuel cost (economy) and emission levels simultaneously while satisfying load demand and operational constraints.

2.4.1. Economy objectives

The fuel cost of a thermal unit is regarded as an essential criterion for economic feasibility. The fuel cost curve is assumed to be approximated by a quadratic function of generator power output P_{gi} as

$$F_1 = \sum_{i=1}^{NG} \left(a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| e_i \sin\left(f_i \left(P_{i\min} - P_i \right) \right) \right| \right) \quad \$/\mathrm{h} \tag{2.4}$$

where a_i ,b_i and c_i are the coefficients and NG is the number of generators. where e_i and f_i are the fuel cost coefficients of unit i with valve-point effect.

2.4.2. Environmental objective

The emission curves 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 emission is given as a quadratic function of generator output P_{gi}, i.e.

$$F_2 = \sum_{i=1}^{NG} \left(\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i + \eta_i \exp(\delta_i P_{gi}) \right) \quad \mathrm{ton/h} \tag{2.5}$$

Where α_i , β_i , Υ_i , η_i and δ_i are the emission coefficients and NG is the number of generators

Multiobjective optimization problem is defined as:

$$\text{Minimize} \qquad [F_1, F_2]^T \tag{2.6}$$

Subjected to

Equality and inequality constraints

where F_1, F_2, are the objectives to be minimized over the set of admissible decision vector P_g.

Equality constraints:

To ensure a real power balance, an equality constraint is imposed, i.e.

$$\sum_{i=1}^{NG} P_{\mathrm{gi}} - (P_D + P_L) = 0 \tag{2.7}$$

where

P_D is the power demand

P_L is the transmission losses, which are approximated in terms of B-coefficients as

$$P_L = B_{oo} + \sum_{i=1}^{NG} B_{io} P_{gi} + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gj} \quad \text{MW} \tag{2.8}$$

where

P_{gi} and P_{gj} are the real power injection at the ith and jth buses, respectively.

B_{oo}, B_{io} and B_{ij} are the loss coefficients which are constants under certain assumed conditions.

Inequality constraints

The inequality constraints imposed on generator output are

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad (i=1,2,......, NG) \tag{2.9}$$

where $P_{gi}^{\min}$ is the lower limit, and $P_{gi}^{\max}$ is the upper limit of generator output.

CHAPTER 3. PARTICLE SWARM OPTIMIZATION

3.1 Introduction

A modern heuristic optimization techniques such as simulated annealing, evolutionary algorithms, neural networks, and ant colony have been given much attention by many researchers due to their ability to find an almost global optimal solution in EDPs [**72**]-[**75**]. One of these modern heuristic optimization paradigms is the particle swarm optimization (PSO) [**76**].

PSO is a kind of evolutionary algorithm based on a population of individuals and motivated by the simulation of social behaviour instead of the survival of the fittest individual. It is a population-based evolutionary algorithm. Similar to the other population-based evolutionary algorithms, PSO is initialized with a population of random solutions. Unlike the most of the evolutionary algorithm solution (individual) in PSO is also associated with a randomized velocity, and the potential solutions, called particles, are then “flown” through the problem space.

The most striking difference between PSO and the other evolutionary algorithms is that PSO chooses the path of cooperation over competition. The other algorithms commonly use some form of decimation, survival of the fittest. In contrast, the PSO population is stable and individuals are not destroyed or created. Individuals are influenced by the best performance of their neighbours. Individuals eventually converge on optimal points in the problem domain. In addition, the PSO traditionally does not have genetic operators like crossover between individuals and mutation, and other individuals never substitute particles during the run. Instead, the PSO refines its search by attracting the particles to positions with good solutions.

Moreover, compared with genetic algorithms (GAs), the information sharing mechanism in PSO is significantly different. In GAs, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only G_{best} (or P_{best}) gives out the information to others. It is a one way information sharing mechanism. The evolution only looks for the best solution. In PSO, all the particles tend to converge to the best solution quickly, comparing with GA, even in the local version in most cases [**75, 76**].

3.2 Basic Particle Swarm Optimization

Particle swarm optimization (PSO) was originally designed and introduced by Eberhart and Kennedy **[3],[76].** The PSO is a population based search algorithm based on the simulation of the social behaviour of birds, bees or a school of fishes. This algorithm originally intends to graphically simulate the graceful and unpredictable choreography of a bird folk. Each individual within the swarm is represented by a vector in multidimensional search space. This vector has also one assigned vector which determines the next movement of the particle and is called the velocity vector.

The PSO algorithm also determines how to update the velocity of a particle. Each particle updates its velocity based on current velocity and the best position it has explored so far and also based on the global best position explored by swarm.

The PSO process then is iterated a fixed number of times or until a minimum error based on desired performance index is achieved. It has been shown that this simple model can deal with difficult optimization problems efficiently.

3.3 Representation of PSO

Let p and v denotes a particle's coordinate (position) and its corresponding flight speed (velocity) in a search space, respectively. Therefore, the jth particle is represented as $P_i = [P_{i1}, P_{i2}, P_{i3}, ..., P_{iNG}]$ in the NP-dimensional space. The best previous position of each particle is recorded and represented as $Pb_i = [Pb_{i1}, Pb_{i2}, Pb_{i3} ... Pb_{iNG}]$. The index of best particle among all the particles in the group is represented by the $[G_1, G_2, G_3, ..., G_{NG}]$. The rate of velocity of the particle is represented as $v_i = [v_{i1}, v_{i2}, v_{i3}, ..., v_{iNP}]$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from Pb_{ij} to G_j as shown in following formulas **[3]**.

$$v_{ij}^{r+1} = w \times v_{ij}^{r} + C_1 \times R_1 \times (Pb_{ij}^{r} - P_{ij}^{r}) + C_2 \times R_2 \times (G_j^{r} - P_{ij}^{r}) \, (i = 1,2,....NP; j = 1,2....,NG) \quad (3.1)$$

$$P_{ij}^{r+1} = P_{ij}^{r} + v_{ij}^{r+1} \quad (i = 1,2,.....NP; j = 1,2.....,NG) \quad (3.2)$$

where

NP is the number of particles in a group
NG is the number of members in a particle
R is the pointer of iteration (generation)
w is the inertia weight factor
C_1 and C_2 are the acceleration constants
R_1 and R_2 are uniform random values in range [0,1]
v_{ij}^{r} is the velocity of j^{th} member of i^{th} particle at r^{th} iteration,
$v_j^{min} \le v_{ij}^{r} \le v_j^{max}$
P_{ij}^{r} is the current position of j^{th} member of i^{th} particle at the r^{th} iteration.

In the above procedure, the parameter $V_j^{\min}$ determined the resolution, or fitness, with which regions are to be searched between the present position and the target position. If $V_j^{\max}$ is too high, particles might fly past good solutions. If $V_j^{\max}$ is too small, particle may not explore sufficiently beyond local solutions. In many experiences with PSO, $V_j^{\max}$ was often set at 10-20% of the dynamic range of the variable on the variable of each dimension.

The constant C_1 and C_2 represents the weighting of the stochastic accerlation terms that pull each particle toward the Pb_{ij}^{r}, G_j^{r} positions. Low values allow particles to roam far from the target region before being tugged back. On the other hand, high values result in abrupt movement toward, or past, target regions. Hence, the acceleration constants C_1 and C_2 were often set to be 2.0 according to past experiences **[3]**.
The above equations are written as

$$v_{ij}^{new} = w \times v_{ij} + C_1 \times R_1 \times (P_{ij}^{best} - P_{ij}) + C_2 \times R_2 \times (G_j^{best} - P_{ij}) \tag{3.3}$$

$$P_{ij}^{new} = P_{ij} + v_{ij}^{new} \quad (i = 1, 2 \ldots NP; j = 1,2 \ldots NG) \tag{3.4}$$

In the strategy of PSO, the particle's best position, P_{ij}^{best} and the global best position $G_{\mathrm{j}}^{\mathrm{best}}$ are the key factors. The best position out of all P_{ij}^{best} is taken as $G_{\mathrm{j}}^{\mathrm{best}}$.Suitable selection of inertia weight in Eq.(3.5) provides balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, w often decrease linearly about 0.9 to 0.4 during a run. In general inertia weight w is set according to the following equation **[3]**:

$$w = w^{\max} - \frac{w^{\max} - w^{\min}}{IT^{\max}} \times IT \tag{3.5}$$

Where

$IT^{\max}$ is the maximum number of iterations(generation) and

IT is the current number of iterations.

3.4 Particle Swarm Optimization Algorithm

According to the discussion in above sections, the following procedure can be used for implementing the PSO algorithm.

- For each particle in the swarm P_i
    - Initialize the particle's position with a uniformly distributed random vector in the lower and upper boundaries of search-space.
    - Evaluate the performance (fitness) of each particle
    - Find the minimum fitness out of each particle performance
    - Assign the particle's best known position(local) to its initial position
    - Assign the Global best position to the swarm's best known position(local) according to the minimum fitness value
    - Initialize the particle's velocity within minimum and maximum boundaries of search-space
- Until a termination criterion is met (e.g. number of iterations performed, or adequate fitness reached), repeat
    - For each particle
        - Create a uniformly distributed random vectors R_1 and R_2
        - Update the particle's velocity: using Eq.(3.3)
        - Update the particle's position by adding the velocity: using Eq.(3.4)

    - Evaluate the performance(fitness) according to new positions:
    - IF the new fitness is less than the previous fitness THEN
        - Update the new particle positions as the particle's best(local) known position
        - Assign new fitness as the local fitness and find the minimum out of each.
        - Update the swarm's best (global best) known position according to minimum fitness.
- Now best new positions hold the best found solution.

CHAPTER 4. MULTIOBJEVTIVE ECONOMIC LOAD DISPATCH OPTIMIZATION USING PSO

4.1 Introduction

The main purpose of the multiobjective generation scheduling is to minimise the economic and emission dispatch simultaneously. In general, power system possesses multiple objectives to be achieved such as economic operations and minimal impact on environment, which inherently have different characteristics, and hence conflicting relations hold among these objectives.

A major objective for the coal-fired power generation loading is to minimize fuel consumption and to maintain emissions within the environmental license limit. Multiobjective problem is converted into scalar problem by using the weighting method. A multi-objective constraint-handling method incorporating the Particle Swarm Optimization (PSO) algorithm has been implemented for the power generation loading optimization application to solve economic-emission load dispatch**.** The particle swarm optimization can be implemented by searching the generation of power plant, P_i within generator limits so that total cost and emission corresponding to that generation become minimum. The best compromise solution is achieved by using the Fuzzy cardinal approach. The multiobjective optimization problem is defined as

Minimize $$F_1 = \sum_{i=1}^{NG} \left(a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| e_i \sin\left(f_i \left(P_{i\min} - P_i \right) \right) \right| \right) \text{\$/h} \tag{4.1a}$$

Minimize $$F_2 = \sum_{i=1}^{NG} \left(\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i + \eta_i \exp(\delta_{\mathrm{i}} P_{gi}) \right) \text{ton/h} \tag{4.1b}$$

Subjected to

$$\sum_{i=1}^{NG} P_{\mathrm{gi}} - (P_D + P_L) = 0 \tag{4.1c}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad (i=1,2,......,NG) \tag{4.1d}$$

Aggregation equations (4.1a) to (4.1d) the multiobjective problem can be written as

Minimize $[F_1(P_g), F_2(P_g)]^T$

Subjected to

$$\sum_{i=1}^{NG} P_{\mathrm{gi}} - (P_D + P_L) = 0 \tag{4.1e}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad (i=1,2,......, NG) \tag{4.1f}$$

Where $F_1(P_g)$, $F_2(P_g)$ are the objectives to be minimized over the set of admissible decision vector P_g

where

NG is the number of generators

a_i, b_i, c_i, e_i and f_i are the cost coefficients

α_i, β_i, Υ_i, η_i and δ_i are the emission coefficients

P_D is the power demand

P_L is the transmission losses which approximated in terms of B- coefficients

The transmission losses are defined as

$$P_L = B_{oo} + \sum_{i=1}^{NG} B_{io} P_{gi} + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gj} \quad \text{MW} \tag{4.2}$$

4.2 Problem Formulation Using Weight Method

To generate the non-inferior solution to the multiobjective problem, the weighted methods is applied. In this method the problem is converted into a scalar optimization as given below **[3]**.

Minimize $$\sum_{k=1}^{M} w_k F_k(P_{gi}) \tag{4.3a}$$

Subjected to $$\sum_{i=1}^{NG} P_{\mathrm{gi}} - (P_D + P_L) = 0 \tag{4.3b}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad (i=1,2,......, NG) \tag{4.3c}$$

$$\sum_{k=1}^{M} w_k = 1 (w_k > 0) \tag{4.3d}$$

where

M is number of objectives

w_k are levels of normalized weights

This approach yields meaningful result to the decision maker when solved many times for different values of w_k (k=1,2,.....M).

4.3 Representation of the Swarm

Since the decision variables of the economic dispatch problem are real power generations, they are used to form the swarm. The set of real power output (*P*) of all the generators is represented as the position of the particle in the swarm. 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 below **[3]**:

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

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

4.4 Initialization of the Swarm

Each element of the swarm matrix is initialized randomly within the real power operating limits based on Eq. (4.1f). The velocities of the particles are initialized randomly according to the following inequality **[3]**:

$$v_j^{min} \leq v_{ij} \leq v_j^{max} \; (i = 1,2,.....NP; \;\; j = 1,2.....,NG) \qquad (4.4)$$

This velocity-initialization scheme always guarantees to produce new particles satisfy real power operating limit constraints. The maximum, minimum velocity limit in the *j*th dimension is computed as:

$$v_j^{\max} = \frac{\left(P_j^{\max} + P_j^{\min}\right)}{\alpha}$$
$$v_j^{\min} = -\frac{\left(P_j^{\max} + P_j^{\min}\right)}{\alpha} \tag{4.5}$$

where α is the chosen number of intervals in the *j*th dimension.

4.5 Initialization of Population

The initial population comprises combination of only the candidate dispatch solutions, which satisfy all the constraints and are feasible solutions of economic dispatch. It consist of P_{ij} (*i=1,2,....NP; j= 1,2 ......NG*). The elements of population are the combination of power outputs of the generating units, which are chosen randomly by a random number ranging over $[P_j^{\min}, P_j^{\max}]$ **[3]**.

$$P_{ij} = P_j^{\min} + rand()(P_j^{\max} - P_j^{\min}) \qquad (i=1,2,...,\ NP;\ j=1,2,....,\ NG) \tag{4.6}$$

where rand() is uniform random number ranging over [0,1].

The elements of P_{ij} may violate constraint Eq.(4.1f) this violation is corrected by fixing them either by lower or upper limit as described below:

$$P_{ij} = \begin{cases} P_j^{\min}\ ; & P_{ij} < P_j^{\min} \\ P_{ij}\ ; & P_j^{\max} \le P_{ij} \le P_j^{\min} \\ P_j^{\max}\ ; & P_{ij} > P_j^{\max} \end{cases} \qquad (\ i=1,2,...,\ NP;\ j=1,2,....,NG\ ) \tag{4.7}$$

4.6 Evaluation of Objective Function

In order to satisfy the power balance constraint, Error is calculated using the power balance equation, which is given by:

$$E = \sum_{j=1}^{NG} P_{ij} - P_D - P_L \qquad (i=1,2,....,NP) \tag{4.8}$$

where

P_D is the demand

P_L are the losses calculated using the Eq.(4.2)

The error as calculated in Eq.(4.8) is now introduced in objective function Eq.(4.1 a), Eq.(4.1 b)to penalize its fitness value. When so introduced the Eq.(4.1 a), Eq.(4.1 b) is changed to the following generalized form:

$$f = F(P_{ij}) + r \times (E)^2 \quad (i=1,2,...NP\ ,j=1,2,......NG) \tag{4.9}$$

where

r is set at higher value

4.7 Initialization of the Best Position

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

4.8 Movement of Particles

The particles in the swarm are accelerated to new positions by adding new velocities to their present positions. The new velocities and new positions are given by Eq.(4.10) and Eq.(4.11) as given below **[3]**.

$$v_{ij}^{new} = w \times v_{ij} + C_1 \times R_1 \times (P_{ij}^{best} - P_{ij}) + C_2 \times R_2 \times (G_j^{best} - P_{ij}) \tag{4.10}$$

$$P_{ij}^{new} = P_{ij} + v_{ij}^{new} \quad (i = 1,2,.....NP;\ j = 1,2.....,NG) \tag{4.11}$$

If any P_{ij} violates the real power operating limit constraints, it is clamped at boundary values using Eq.(4.7).

4.9 Updating the Best

The particles are evaluated in the positions by objective function values, the best P_{ij}^{best} is taken as G_j^{best}. An objective value at G_j^{best} is saved as f_{best}.

4.10 Stopping Criterion

There are various criteria available to stop a stochastic algorithm. Some examples 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. If the stopping criterion is not satisfied, the above procedure is repeated with incremented IT value. Otherwise, G_j^{best} is the optimum generation schedule and f_{best} is the minimum generation cost of the economic dispatch problem **[3]**.

4.11 Decision Making

Considering the imprecise nature of the decision maker's judgment, it is natural to assume that the decision maker may have fuzzy or imprecise goals for each objective functions. The fuzzy sets are defined by equation called membership functions. These functions represent the degree of membership in some fuzzy sets using valves from 0 to 1. The membership value 0, indicates incompatibility with sets, while 1 means full compatibility. By taking account of the minimum and maximum values of each objective function together with rate of increase of membership satisfaction, the decision maker must detect membership function $\mu(F_i)$ is strictly monotonic decreasing and continuous functions defined as**[3].**

$$\mu(F_i) = \begin{cases} 1 & ; \quad F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & ; F_i^{\max} < F_i < F_i^{\min} \\ 0 & ; \quad F_i \ge F_i^{\max} \end{cases} \tag{4.12}$$

The value of membership function suggests how far (in the scale from 0 to 1) a non-inferior solution has satisfied the F_i objective. The sum of membership function values $\mu(F_i)$ ($i = 1,2,\ldots\ldots M$) for all the objective can computed in order to measure the accomplishment of each solution in satisfying the objectives. The accomplishment of each non-dominated solution can be rated with respect to all the K non-dominated solutions by normalizing its accomplishment over the sum of the accomplishment of K non-dominated solution as follows:

$$\mu_D^K = \frac{\left[\sum_{i=1}^{M} \mu(F_i^K)\right]}{\left[\sum_{i=1}^{k}\sum_{i=1}^{M} \mu(F_i^K)\right]} \tag{4.13}$$

The function μ_D in (4.13) can be treated as a membership function for non-dominated solution, in a fuzzy set and represented as fuzzy cardinal ranking of the non-dominated solutions. The solution that attains the maximum membership μ_D^K, in the fuzzy set so obtained can be chosen as ‘best’ solution or the one having highest cardinal priority ranking.

$$\text{Max}\left[\mu_D^K : k = 1,2,........K\right] \tag{4.14}$$

4.12 Algorithm for the problem formulation is given as follow:

1. Read data: viz. cost coefficients, Emission coefficients, maximum allowed iterations ITMAX, population size, $P_i^{\min}$ and $P_i^{\max}$ $(i = 1,2,....,NG)$ etc.
2. Generate an array of $(NP \times NG)$ size of uniform random numbers.
3. Initialize randomly the individuals of the population according to the limit of each unit including individual dimensions, searching points, and velocities.

   DO
4. $w_1 = 1$, $w_2 = 1 - w_1$
5. Set particle (bird) counter, $i = 0$

   DO
6. Increment particle counter, $i = i+1$
7. Set generation counter, $j = 0$

   DO
8. Increment the generation counter, $j = j + 1$
9. Initialize $P_{ij}^{best} = P_{ij}$
10. WHILE (j<NG)
11. Compute $F(P_{ij})$ using following equation

    $F(P_{ij}) = (w_1 F_1 + w_2 F_2)$
12. Compute E using Eq.(4.8) and f_i using the following equation

    $f_i = F(P_{ij}) + r \times (E)^2$
13. Initialize $f_{ij}^{best} = f_{ij}$

    WHILE (i < NP)
14. Set particle counter, $i = 1$, $f^{global} = f_i^{best}$

    DO
15. Increment particle counter, $i = i+1$
16. IF $(f_i^{best} < f^{global})$ THEN set $f^{global} = f_i^{best}$ and $G_j^{best} = P_{ij}^{best}$ $(j=1,2,.....,NG)$

```
    WHILE ($i$ < NP)
17. Set iteration counter, IT=0
    DO
18. Increment iteration counter, IT=IT+1
19. Compute $w = w^{\max} - \frac{w^{\max} - w^{\min}}{IT^{\max}} \times IT$
20. Set particle (bird) counter, $i$=0
    DO
21. Increment particle counter, $i$=$i$+1
22. Set generation counter, $j$=0
    DO
23. Increment generation counter, $j$=$j$+1
24. Generate the velocity of particle
25. Compute $V_{ij}^{new}$ using Eq. (4.10)
26. IF ($V_{ij}^{new} > V_j^{\max}$) THEN update $V_{ij}^{new} = V_j^{\max}$
27. IF ($V_{ij}^{new} < V_j^{\min}$) THEN update $V_{ij}^{new} = V_j^{\min}$
28. Compute $P_{ij}^{new}$ using following equation
     $P_{ij}^{new} = P_{ij} + V_{ij}^{new}$
    WHILE ($j$<$NG$)
29. Compute $F(P_{ij}^{new}) = (w_1 F_1 + w_2 F_2)$
30. Compute $E$ for new values of positions using Eq.(4.8) and $f_i^{new}$ using the following
    equation
    $f_i^{new} = F(P_{ij}^{new}) + r \times (E)^2$
31. IF ($f_i^{new} < f_i^{best}$) THEN set $f_i^{best} = f_i^{new}$ and $P_{ij}^{best} = P_{ij}^{new}$   ($j$=1,2,....,$NG$)
    WHILE ($i$<$NP$)
32. Set particle counter, $i$=1, $f^{\min} = f_i^{best}$
    DO
33. Increment generation counter, $j$=$j$+1
34. IF ($f_i^{best} < f^{\min}$) THEN set $f^{\min} = f_i^{best}$ and $P_j^{\min} = P_{ij}^{best}$  ($j$=1,2,....,$NG$)
    WHILE ($i$ < $NP$)
35. Set particle (bird) counter, $i$=0
```

```
DO
36. Increment particle counter, $i=i+1$
37. Set generation counter, $j=0$
DO
38. Increment the generation counter, $j=j+1$
39. Set $V_{ij} = V_{ij}^{new}$
40. Set $P_{ij} = P_{ij}^{new}$
WHILE ($j<NG$)
41. IF $(f^{\min} < f^{global})$ THEN set $f^{global} = f^{\min}$ and $G_{ij}^{best} = P_{ij}^{best}$ $(j=1,2,....,NG)$
WHILE $(IT < IT^{MAX})$
DO
42. Compute $F_1$ and $F_2$ respectively corresponding to global best value.
43. $w_1 = w_1 - 0.1$
WHILE $(w_1 < 0)$
44. Compute membership function $\mu(F_i)$ from Eq.(4.13)
45. Compute the fuzzy cardinal priority $\mu_D^k$ of the non-dominated solutions from Eq.(4.14)
46. Select the solution that attains the maximum membership $\mu_D^k$ in the fuzzy set so obtained.
47. STOP
```

CHAPTER 5. RESULTS AND DISCUSSION

In this research work, the results have been obtained from the developed algorithm for multi-objective power dispatch based on PSO, which has been discussed in Chapter-4. The developed algorithm has been tested on three test systems **[55]**. Input data are also given in APPENDIX – I, II and III respectively. As explained in Chapter-4, multiobjective power dispatch problem has been formed with the combinations of economic dispatch, emission dispatch which are formulated with objective of minimizing fuel cost, emissions. Keeping the above, the following cases have been studied –Case Study 1: For 6 generating units. Case Study 2: For 10 generating units. Case Study 3: For 40 generating units

The simulation has been carried out on system having 2.40 GHz intel (R) Core(TM) i5 processor with 3 GB of RAM in Fortran power station 4.0.

5.1 Case Study 1: Economic, Emission and Multi-objective economic emission dispatch (EED) for 6 generating units.

In this case study, developed algorithm has been applied for economic dispatch, emission dispatch and multi-objective economic emission dispatch (EED) for 6 generating units. The inputs parameters are taken from APPENDIX I. To find the best solution, the programme has run at different value of w_1 and w_2, the total cost and emission are calculated corresponding to these weights. After calculating the cost and emission, the membership functions (μ_1, μ_2) and then membership function for non-dominated solutions (μ_D) are calculated. The simulation results obtained are given in Table 5.1.

Table 5.1- Cost, emission, μ_1, μ_2 and μ_D of six-unit system for power demand (P_D) = 1200MW at different values of w_1 and w_2.

Sr.No	w_1	w_2	Cost ($/h)	Emission (ton/h)	μ_1	μ_2	μ_D
1	1	0	64098.6	1345.578	1	0	0.08811

2	0.9	0.1	64098.8	1345.500	0.9998	0.00074	0.08816
3	0.8	0.2	64099.4	1345.28	0.9995	0.0028	0.08831
4	0.7	0.3	64100.7	1344.5	0.9988	0.0102	0.08890
5	0.6	0.4	64105.0	1343.8	0.9966	0.0168	0.08929
6	0.5	0.5	64110.0	1342.0	0.9939	0.034	0.09051
7	0.4	0.6	64123.4	1339.0	0.9813	0.062	0.09192
8	0.3	0.7	64190.8	335.5	0.9510	0.095	0.09216
9	0.2	0.8	64300.6	1330.8	0.8932	0.1404	0.09107
10	0.1	0.9	64887.88	1283.401	0.5829	0.5909	0.10342
11	0	1	65991.2500	1240.369	0	1	0.08811

As seen from the table, When $w_1 = 1$ and $w_2 = 0$, the total generation cost comes out to be minimum (Economic load dispatch) at the expense of increase in emission. When w_1 approaches 1 to 0 and w_2 approaches 0 to 1, the total emission comes out to be minimum (Emission dispatch) at the expense of increase in cost. To find the best solution (multiobjective generation scheduling) the fuzzy cardinal ranking method is applied. The maximum value of μ_D gives the best solution. For this problem, at $w_1 = 0.1$ and $w_2 = 0.9$ gives the best solution.

The power generation correspond to Economic load dispatch, Emission dispatch and Multiobjective economic emission dispatch is shown in the table 5.2.

Table 5.2- Shows generation (P_G), cost, emission of six-unit system problem for power demand (P_D) = 1200MW

P_G(MW)	Economic dispatch	Emission dispatch	EED
P_1(MW)	84.624470	125.000000	100.777700
P_2(MW)	93.414930	150.000000	124.132300
P_3(MW)	210.000000	200.829900	208.526200
P_4(MW)	225.000000	199.620900	204.681800
P_5(MW)	315.000000	288.011500	308.903600
P_6(MW)	325.000000	286.694500	304.415400
Cost($/h)	64098.6000	65991.250000	64836.81000
Emission(ton/h)	1345.5780	1240.369000	1286.46000

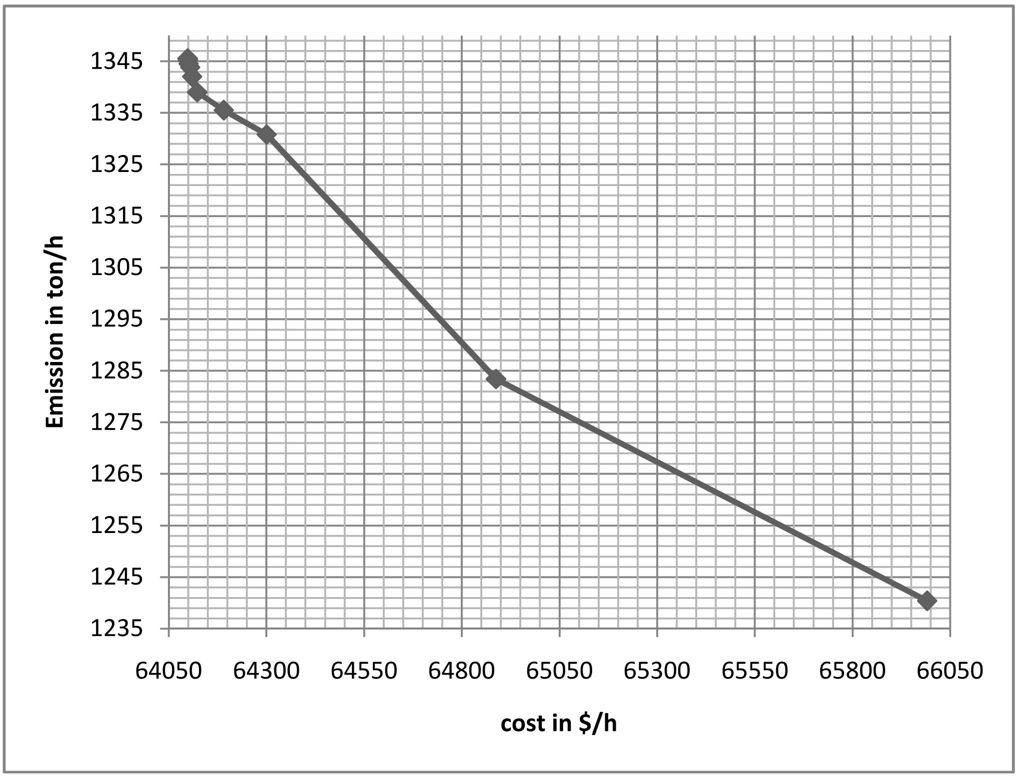

Fig:5.1 : Conflicting nature of objectives (economy and emission) for 6-genrating units system.

From the fig:5.1, it is clear that as the weight w_1 approaches 1 to 0 and w_2 approaches 0 to 1, Cost has increased from 64098.6 $/h to 65991.250 $/h with the decreased in emission from 1345.578 ton/h to 1240.369 ton/h, which shows that both objectives are conflicting in nature.

5.2 **Case Study 2:** Economic, Emission and Multi-objective economic emission dispatch (EED) for 10 generating units.

In this case study, developed algorithm has been applied for economic dispatch, emission dispatch and multi-objective economic emission dispatch (EED) for 10 generating units. The inputs parameters are taken from APPENDIX II. To find the best solution, the programme is run at different value of w_1 and w_2 and the total cost and emission are calculated corresponding to these weights. After calculating the cost and emission, the μ_1, μ_2 and then μ_D are calculated. The simulation results obtained are given in Table 5.3.

Table 5.3- Cost, emission, μ_1, μ_2 and μ_D of 10-unit system for power demand (P_D)= 2000MW at different values of w_1 and w_2.

Sr.No	w_1	w_2	Cost ($/h)	Emission (ton/h)	μ_1	μ_2	μ_D
1	1	0	111484.9000	4570.9070	1	0	0.08254
2	0.9	0.1	111485.600	4560.2360	0.99985	0.01668	0.083913
3	0.8	0.2	111487.500	4550.2270	0.99947	0.03234	0.085174
4	0.7	0.3	111492.800	4535.1710	0.99839	0.05589	0.087029
5	0.6	0.4	111500.800	4520.8960	0.99676	0.07821	0.088737
6	0.5	0.5	111515.700	4502.8650	0.99373	0.10641	0.09081
7	0.4	0.6	111546.200	4478.3510	0.98753	0.14475	0.09346

8	0.3	0.7	111598.500	4450.963	0.97689	0.18759	0.096126
9	0.2	0.8	112837.400	4253.809	0.72487	0.49594	0.10077
10	0.1	0.9	113421.800	4114.019	0.60600	0.71457	0.10901
11	0	1	116400.900	3931.524	0	1	0.08254

As seen from the table, When $w_1 = 1$ and $w_2 = 0$, the total generation cost comes out to be minimum (Economic load dispatch) at the expense of increase in emission. When w_1 approaches zero and w_2 approaches 1, the total emission comes out to be minimum (Emission dispatch) at the expense of increase in cost. To find the best solution (multiobjective generation scheduling) the fuzzy cardinal ranking method is applied. The maximum value of μ_D gives the best solution. For this problem, at $w_1 = 0.1$ and $w_2 = 0.9$ gives the best solution.

The power generation correspond to Economic load dispatch, Emission dispatch and Multiobjective economic emission dispatch is shown in the table 5.4.

Table 5.4 Shows generation (P_G), cost, emission of Ten-unit system for P_D = 2000MW

P_G(MW)	Economic dispatch	Emission dispatch	EED
P_1(MW)	55.000000	55.000000	54.960300
P_2(MW)	80.000000	79.999930	80.000000
P_3(MW)	106.589400	81.153810	82.268850
P_4(MW)	100.704600	81.306880	86.075310
P_5(MW)	81.765650	160.000000	143.975300
P_6(MW)	82.776970	240.000000	161.209000
P_7(MW)	300.000000	294.473500	300.000000
P_8(MW)	340.000000	297.118200	309.380200
P_9(MW)	470.000000	396.836400	433.635300
P_{10}(MW)	470.000000	395.505500	432.244500
Cost($/h)	111484.900	116400.900000	113421.60000
Emission(ton/h)	4570.907	3931.524000	4114.60000

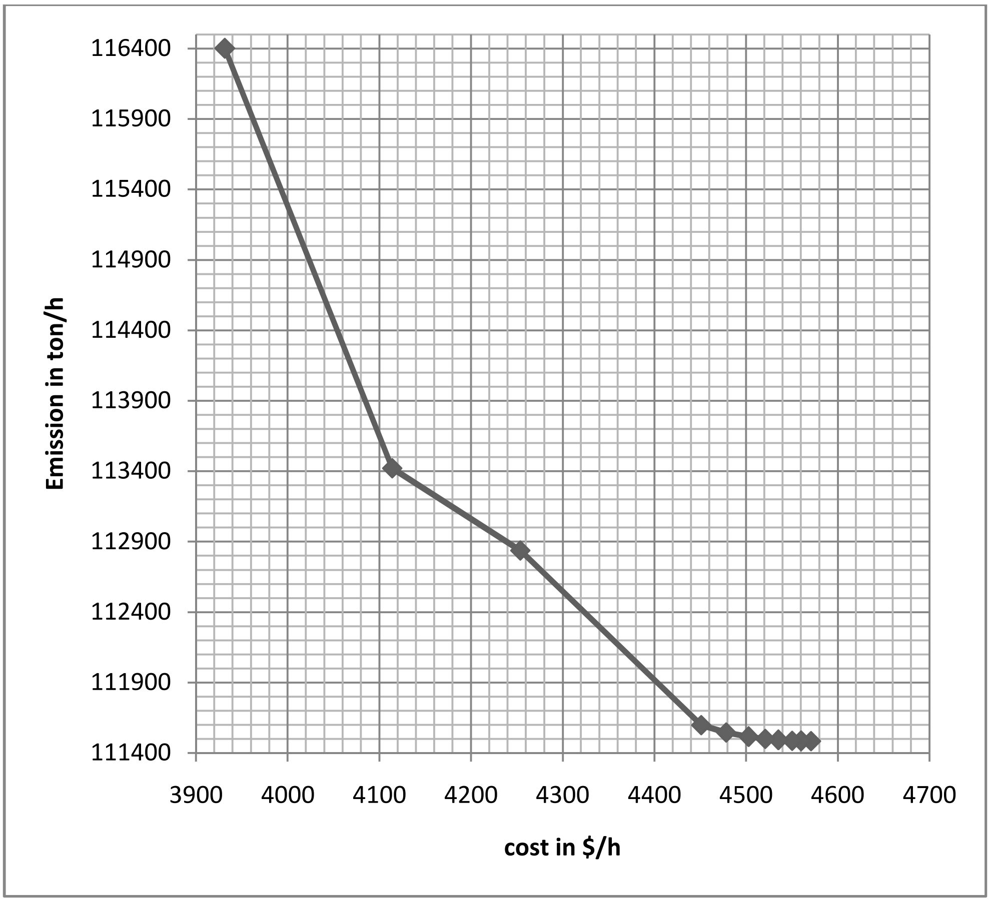

Fig: 5.2. Conflicting nature of objectives for 10-generating unit system

From the fig:5.2, it is clear that as the weight w_1 approaches 1 to 0 and w_2 approaches 0 to 1, Cost has increased from 111484.9000 $/h to 116400.9000 $/h with the decreased in emission from 4570.9070 ton/h to 3931.524 ton/h, which shows that both objectives are conflicting in nature.

5.3 Case Study 3: Economic, Emission and Multi-objective economic emission dispatch (EED) for 40 generating units.

In this case study, developed algorithm has been applied for economic dispatch, emission dispatch and multi-objective economic emission dispatch (EED) for 40 generating units. The inputs parameters are taken from APPENDIX III. To find the best solution, the programme has run at different value of w_1 and w_2 and the total cost and emission are calculated corresponding to these weights. After calculating the cost and emission, the μ_1, μ_2 and then μ_D are calculated. The simulation results obtained are given in Table 5.5.

Table 5.5- Cost, emission, μ_1, μ_2 and μ_D of forty-unit system for power demand (P_D) = 10500MW at different values of w_1 and w_2

Sr.No	w_1	w_2	Cost ($/h)	Emission (ton/h)	μ_1	μ_2	μ_D
1	1	0	122630.100	358748.00	1	0	0.080377
2	0.9	0.1	125730.300	195254.80	0.57848	0.89807	0.11868
3	0.8	0.2	127093.100	189206.30	0.39319	0.93129	0.10645
4	0.7	0.3	128289.300	182934.80	0.23055	0.96574	0.096154
5	0.6	0.4	128957.700	179059.00	0.13967	0.98703	0.09056
6	0.5	0.5	129162.500	178948.10	0.11183	0.98764	0.08837
7	0.4	0.6	129262.200	178727.90	0.09827	0.98885	0.08737
8	0.3	0.7	129469.500	178434.50	0.07008	0.99046	0.08555
9	0.2	0.8	129620.700	177722.20	0.04953	0.994378	0.08390
10	0.1	0.9	129764.600	177367.60	0.02996	0.99632	0.08248
11	0	1	129985.00	176698.80	0	1	0.080377

As seen from the table, When $w_1 = 1$ and $w_2 = 0$, the total generation cost comes out to be minimum (Economic load dispatch) at expense of increase in emission. When W_1 approaches zero and W_2 approaches 1, the total emission comes out to be minimum (Emission dispatch) at expense of rise in cost. To find the best solution (multiobjective generation scheduling) the fuzzy cardinal ranking method is applied. The maximum value of μ_D gives the best solution. For this problem, at $w_1 = 0.9$ and $w_2 = 0.1$ gives the best solution.

The power generation correspond to Economic load dispatch, Emission dispatch and Multiobjective economic emission dispatch is shown in the table 5.6.

Table 5.6 Shows Generation, cost, emission of Forty-unit system for P_D =10500MW

P_G(MW)	Economic dispatch	Emission dispatch	EED
P_1(MW)	114.000000	114.000000	114.000000
P_2(MW)	114.000000	114.000000	114.000000
P_3(MW)	97.399830	120.000000	120.000000
P_4(MW)	190.000000	169.288500	179.733100
P_5(MW)	97.000000	97.000000	97.000000
P_6(MW)	105.400100	124.156000	140.000000
P_7(MW)	184.799800	300.000000	300.000000
P_8(MW)	284.599700	300.000000	300.000000
P_9(MW)	284.599700	300.000000	300.000000
P_{10}(MW)	204.799300	130.000000	130.000000
P_{11}(MW)	293.429000	298.152100	318.396700
P_{12}(MW)	168.799700	297.730400	318.398400
P_{13}(MW)	125.000000	433.421900	394.280300
P_{14}(MW)	394.279400	421.314300	394.280300
P_{15}(MW)	304.519700	422.618100	394.279700
P_{16} (MW)	394.279200	422.273800	394.279500
P_{17}(MW)	500.000000	439.253800	489.276200
P_{18}(MW)	489.279400	439.120900	489.264900
P_{19}(MW)	511.279600	439.335200	423.108600
P_{20}(MW)	511.279600	439.131600	425.103900
P_{21}(MW)	523.279500	439.375300	434.884600
P_{22}(MW)	523.279400	439.139900	434.385600
P_{23}(MW)	523.279700	439.345500	434.434000
P_{24}(MW)	523.279700	439.639900	435.048600
P_{25}(MW)	523.279200	439.774700	433.901200
P_{26}(MW)	523.279400	439.995500	433.580100
P_{27}(MW)	10.000000	28.803960	11.914430
P_{28}(MW)	10.000000	28.798590	11.908050
P_{29}(MW)	10.000090	28.951430	12.024250
P_{30}(MW)	87.800500	97.000000	97.000000
P_{31}(MW)	159.733300	172.189000	190.000000
P_{32}(MW)	190.000000	172.356000	190.000000
P_{33}(MW)	159.733300	172.219300	190.000000
P_{34}(MW)	164.800400	200.000000	200.000000
P_{35}(MW)	200.000000	200.000000	200.000000
P_{36}(MW)	200.000000	200.000000	200.000000
P_{37}(MW)	89.114840	100.749500	110.000000
P_{38}(MW)	110.000000	100.714400	110.000000
P_{39}(MW)	89.114000	100.802300	110.000000
P_{40}(MW)	511.279800	439.341300	425.514400
Cost($/h)	122630.100000	129985.000000	125730.300000
Emission(ton/h)	358748.700000	176698.800000	195254.800000

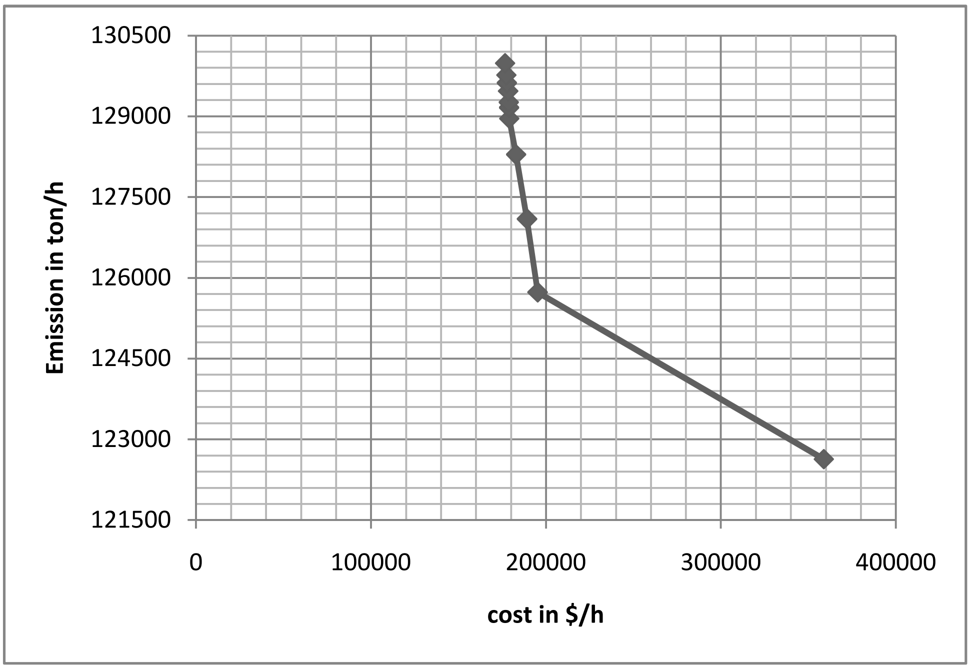

Fig: 5.3, Conflicting nature of objectives for 40-generating units

From the fig:5.3, it is clear that as the weight w_1 approaches 1 to 0 and w_2 approaches 0 to 1, Cost has increased from 122630.100 $/h to 129985.00 $/h with the decreased in emission from 358748.00ton/h to 176698.80 ton/h, which shows that both objectives are conflicting in nature.

5.4 Comparison with different techniques shows the effectiveness of applied method

To show the effectiveness of the PSO method, three systems are investigated for each kind of problem (Economic, Emission and multiobjective). For each problem results are compared with related work carried out by various researchers.

5.4.1. Economic dispatch problem

Economic dispatch problem is formulated for three systems consisting of 6 generators,10 generators and 40 generators. Table, 5.7 shows the comparison of results obtained by PSO, differential evolution DE **[55]** **,** classical evolutionary programming(CEP), fast evolutionary programming(FEP), mean(FEP) and improved(FEP) **[32].** Results obtained for 6, generating units are found comparable with the DE **[55]**, for 10 generating units results obtained by applied method are found better then DE **[55]**. The results obtained for 40 generating units by

PSO method are found better than CEP **[32]**, FEP **[32]** and mean FEP **[32]** ,whereas compared with improved FEP **[32]** found almost similar.

Table 5.7: Comparison of generation cost ($/h) of the 6, 10 and 40 generating units systems with valve point loading.

Number of generating units	6	10	40
Cost($/h) DE[55]	64083.000	111500.00	-
Cost($/h) CEP[32]	-	-	123488.29
Cost($/h) FEP[32]	-	-	122679.10
Cost($/h) mean FEP[32]	-	-	122647.57
Cost($/h) improved FEP[32]	-	-	122624.34
Cost($/h) PSO	64098.600	111484.90	122630.10

5.4.2. Emission dispatch Problem

Emission dispatch problem is formulated for three systems consisting of 6 generators, 10 generators and 40 generators. Table, 5.8 shows the comparison of results obtained by PSO and differential evolution DE **[55]** method for 6, 10 and 40 generating units. The results obtained by applied method for 6-generators are found almost similar with the DE **[55]**. Results obtained from 10 generating units found higher (0.2%) then DE **[55].**The results obtained for 40 generating units from applied method are found comparable with results obtained by DE **[55].**

Table 5.8: Comparison of emission dispatch (ton/h) of 6, 10 and 40 generating units system

Number of generating units	6	10	40
Emission(ton/h) DE[55]	1240.700	3923.40	176680
Emission(ton/h) PSO	1240.369	3931.524	176698.8

5.4.3. Multiobjective economic-emission dispatch(EED)

Multiobjective EED problem is formulated for 6, 10 and 40 generating units. Table 5.9 shows the comparison of results obtained from PSO and other techniques such as multi objective differential evolution (MODE) **,** pareto differential evolution (PDE), non dominated sorting genetic algorithm-II (NSGA-II) and strength pareto evolutionary algorithm 2 (SPEA 2)**[55].**

(I). Comparison for 6-generator units

The results obtained from PSO for 6 generating units, when compared with MODE **[55]**, shows that emission is decreased by 0.233% at the expense of 0.06% in economy. When Compared with PDE **[55]**, shows that operating cost is decreased by 0.05% at the expense of rise in emission by 0.18%.When compared with NSGAII **[55]**, shows that operating cost is decreased by 0.1% at the expense of rise in emission by 0.18%. When compared with SPEA2 **[55]**, shows that emission is decreased by 0.12% at the expense of 0.005% in economy

(II). Comparison for 10 generating units

The results obtained from PSO for 10 generating units, when compared with MODE **[55]**, shows that operating cost and the emission both are decreased by 0.05% and 0.26%. When Compared with PDE **[55]**, shows that operating cost is decreased by 0.077% at the expense of rise in emission by -0.06%.When compared with NSGAII **[55]**, results shows that operating cost and the emission decreased by 0.1% and 0.4%, When compared with SPEA2 **[55]** , shows that operating cost is decreased by 0.08% at the expense of rise in emission by 0.01%.

(III). Comparison for 40 generating units

The results obtained from PSO for 40 generating units when compared with MODE **[55]**, shows that operating cost and the emission decreased by 0.047% and 8.16%. When Compared with PDE **[55]**, results shows that emission is decreased by 8.45% at the same cost. When compared with NSGAII **[55]** and SPEA2 **[55]**, results shows that operating cost and the emission both are decreased by 0.063% and 8.115%,

Table5.9: Comparison of best compromise solution for multiobjective problem for 6,10 and 40 generating units.

Sr.No	PSO		MODE[55]		PDE[55]		NSGA II[55]		SPEA 2[55]	
	Cost ($/h)	Emisssion (ton/h)	Cost ($/h)	Emission (ton/h)	Cost ($/h)	Emission (ton/h)	Cost ($/h)	Emission (ton/h)	Cost ($/h)	Emission (ton/h)
TEST 1	64887.88	1283.401	64843.00	1286.00	64920.00	1281.00	64962.00	1281.00	64884.00	1285.00
TEST 2	113421.6	4114.019	113480.00	4124.90	113510.00	4111.40	11354.00	4130.20	11352.00	4109.00
TEST 3	125730.3	195254.80	125790.00	211190.00	125730.00	211770.00	125810.00	211100.00	125810.00	211100.00

CHAPTER 6. CONCLUSION AND SCOPE FOR FUTURE WORK

6.1. Conclusion

The multi objective power dispatch problem has been solved using an algorithm based on particle swarm optimization (PSO). First the problem is converted into scalar form by applying weighting method. The best solution is calculated using Fuzzy cardinal approach. Economic dispatch, emission-dispatch and multiobjective problems have been solved for systems having six generators, ten generators and forty generators using this algorithm.

Results obtained from applied approach are compared with different approaches and following conclusion are drawn from the study.

- The developed algorithm is capable to handle different competing objectives.
- The results drawn from applied approach are found satisfactory for economic and emission dispatch problems as compared with differential evolution (DE), classical evolutionary programming (CEP), fast evolutionary programming (FEP), mean (FEP) and improved (FEP).
- The results drawn from applied approach are found better for Multiobjective problem as compared with multiobjective differential evolution (MODE) technique, pareto differential evolution (PDE), non dominated sorting genetic algorithm-II (NSGA-II) and strength pareto evolutionary algorithm 2 (SPEA 2).

6.2. Scope For Future Work

The scope of work after studying Power Dispatch using PSO is identified as:

- This problem can be applied to Practical Systems.
- Multiobjective particle swarm optimization (MOPSO) algorithm can be used to solve the problem.
- Extend the problem by incorporating more than two objectives.

APPENDIX

APPENDIX-1,

1. Input data for 6-generating unit:

Unit	Pmax	Pmin	a_i	b_i	c_i	α_i	β_i	Υ_i
1	10	125	756.9888	38.5390	0.15247	13.8593	0.3267	0.00419
2	10	150	451.3251	46.1591	0.10587	13.8593	0.3267	0.00419
3	35	210	1243.5311	38.3055	0.03546	40.2699	-0.54551	0.00683
4	35	225	1049.9977	40.3965	0.02803	40.2699	-0.54551	0.00683
5	125	315	1356.6592	38.2704	0.01799	42.8955	-0.51116	0.00461
6	130	325	1658.5696	36.3278	0.02111	42.8955	-0.51116	0.00461

2. B-Coefficients for 6- generator units:

$$B = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

APPENDIX-2

1. Input data for 10 generating units

Unit			a_i	b_i	c_i	d_i	e_i	α_i	β_i	Υ_i	η_i	δ_i
1	10	55	1000.403	40.5407	0.12951	33	0.0174	360.0012	-3.9864	0.04702	0.25475	0.01234
2	20	80	950.606	39.5804	0.10908	25	0.0178	350.0056	-3.9524	0.04652	0.25475	0.01234
3	47	120	900.705	36.5104	0.12511	32	0.0162	330.0056	-3.9023	0.04652	0.25163	0.01215
4	20	130	800.705	39.5104	0.12111	30	0.0168	330.0056	-3.9023	0.04652	0.25163	0.01215
5	50	160	756.799	38.5390	0.15247	30	0.0148	13.8593	0.3277	0.00420	0.24970	0.01200
6	70	240	451.325	46.1592	0.10587	20	0.0163	13.8593	0.3277	0.00420	0.24970	0.01200
7	60	300	1243.531	38.3055	0.03546	20	0.0152	40.2699	-0.5455	0.00680	0.24800	0.01290
8	70	340	1049.998	40.3965	0.02803	30	0.0128	40.2699	-0.5455	0.00680	0.24990	0.01203
9	135	470	1658.569	36.3278	0.02111	60	0.0136	42.8955	-0.5112	0.00460	0.25470	0.01234
10	150	470	1356.659	38.2704	0.01799	40	0.0141	42.8955	-0.5112	0.00460	0.25470	0.01234

2. B-coefficients for 10 generating units:

$$B = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000016 & 0.000017 & 0.000017 & 0.000018 & 0.000019 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000016 & 0.000017 & 0.000015 & 0.000015 & 0.000016 & 0.000018 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 & 0.000012 & 0.000014 & 0.000014 & 0.000016 & 0.000016 \\ 0.000015 & 0.000016 & 0.000010 & 0.000040 & 0.000014 & 0.000010 & 0.000011 & 0.000012 & 0.000014 & 0.000015 \\ 0.000016 & 0.000017 & 0.000012 & 0.000014 & 0.000035 & 0.000011 & 0.000013 & 0.000013 & 0.000015 & 0.000016 \\ 0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000011 & 0.000036 & 0.000012 & 0.000012 & 0.000014 & 0.000015 \\ 0.000017 & 0.000015 & 0.000014 & 0.000011 & 0.000013 & 0.000012 & 0.000038 & 0.000016 & 0.000016 & 0.000018 \\ 0.000018 & 0.000016 & 0.000014 & 0.000012 & 0.000013 & 0.000012 & 0.000016 & 0.000040 & 0.000015 & 0.000016 \\ 0.000019 & 0.000018 & 0.000016 & 0.000014 & 0.000015 & 0.000014 & 0.000016 & 0.000015 & 0.000042 & 0.000019 \\ 0.000020 & 0.000018 & 0.000016 & 0.000015 & 0.000016 & 0.000015 & 0.000018 & 0.000016 & 0.000019 & 0.000044 \end{bmatrix}$$

APPENDIX-3

1. Input data for 40 generating units:

No.			a_i	b_i	c_i	d_i	e_i	α_i	β_i	Υ_i	η_i	δ_i
1	36	114	94.705	6.73	0.00690	100	0.084	60	-2.22	0.0480	1.3100	0.05690
2	36	114	94.705	6.73	0.00690	100	0.084	60	-2.22	0.0480	1.3100	0.05690
3	60	120	309.540	7.07	0.02028	100	0.084	100	-2.36	0.0762	1.3100	0.05690
4	80	190	369.030	8.18	0.00942	150	0.063	120	-3.14	0.0540	0.9142	0.04540
5	47	97	148.890	5.35	0.01140	120	0.077	50	-1.89	0.0850	0.9936	0.04060
6	68	140	222.330	8.05	0.01142	100	0.084	80	-3.08	0.0854	1.3100	0.05690
7	110	300	287.710	8.03	0.00357	200	0.042	100	-3.06	0.0242	0.6550	0.02846
8	135	300	391.980	6.99	0.00492	200	0.042	130	-2.32	0.0310	0.6550	0.02846
9	135	300	455.760	6.60	0.00573	200	0.042	150	-2.11	0.0335	0.6550	0.02846
10	130	300	722.820	12.9	0.00605	200	0.042	280	-4.34	0.4250	0.6550	0.02846
11	94	375	635.200	12.9	0.00515	200	0.042	220	-4.34	0.0322	0.6550	0.02846
12	94	375	654.690	12.8	0.00569	200	0.042	225	-4.28	0.0338	0.6550	0.02846
13	125	500	913.400	12.5	0.00421	300	0.035	300	-4.18	0.0296	0.5035	0.02075
14	125	500	1760.400	8.84	0.00752	300	0.035	520	-3.34	0.0512	0.5035	0.02075
15	125	500	1760.400	8.84	0.00752	300	0.035	510	-3.55	0.0496	0.5035	0.02075
16	125	500	1760.400	8.84	0.00752	300	0.035	510	-3.55	0.0496	0.5035	0.02075
17	220	500	647.850	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075
18	220	500	649.690	7.95	0.00313	300	0.035	222	-2.66	0.0151	0.5035	0.02075
19	242	550	647.830	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075
20	242	550	647.810	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075
21	254	550	785.960	6.63	0.00298	300	0.035	290	-2.22	0.0145	0.5035	0.02075
22	254	550	785.960	6.63	0.00298	300	0.035	285	-2.22	0.0145	0.5035	0.02075
23	254	550	794.530	6.66	0.00284	300	0.035	295	-2.26	0.0138	0.5035	0.02075
24	254	550	794.530	6.66	0.00284	300	0.035	295	-2.26	0.0138	0.5035	0.02075
25	254	550	801.320	7.10	0.00277	300	0.035	310	-2.42	0.0132	0.5035	0.02075
26	254	550	801.320	7.10	0.00277	300	0.035	310	-2.42	0.0132	0.5035	0.02075

27	10	150	1055.100	3.33	0.52124	120	0.077	360	-1.11	1.8240	0.9936	0.04060
28	10	150	1055.100	3.33	0.52124	120	0.077	360	-1.11	1.8420	0.9936	0.04060
29	10	150	1055.100	3.33	0.52124	120	0.077	360	-1.11	1.8420	0.9936	0.04060
30	47	97	148.890	5.35	0.01140	120	0.077	50	-1.89	0.0850	0.9936	0.04060
31	60	190	222.920	6.43	0.00160	150	0.063	80	-2.08	0.0121	0.9142	0.04540
32	60	190	222.920	6.43	0.00160	150	0.063	80	-2.08	0.0121	0.9142	0.04540
33	60	190	222.920	6.43	0.00160	150	0.063	80	-2.08	0.0121	0.9142	0.04540
34	90	200	107.870	8.95	0.00010	200	0.042	65	-3.48	0.0012	0.6550	0.02846
35	90	200	116.580	8.62	0.00010	200	0.042	70	-3.24	0.0012	0.6550	0.02846
36	90	200	116.580	8.62	0.00010	200	0.042	70	-3.24	0.0012	0.6550	0.02846
37	25	110	307.450	5.88	0.01610	80	0.098	100	-1.98	0.0950	1.4200	0.06770
38	25	110	307.450	5.88	0.01610	80	0.098	100	-1.98	0.0950	1.4200	0.06770
39	25	110	307.450	5.88	0.01610	80	0.098	100	-1.98	0.0950	1.4200	0.06770
40	242	550	647.830	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075

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