Multi Objective Economic Emission Dispatch Using Modified Multi Objective Particle Swarm Optimization

A Dissertation

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CERTIFICATE

This is to certify that the dissertation entitled **"Multi Objective Economic Emission Dispatch Using Modified Multi Objective Particle Swarm Optimization"** is an authentic record of my own work carried out as per requirements for the award of degree of **Master of Engineering** in **Power Systems & Electric Drives** submitted in Electrical and Instrumentation Engineering Department at Thapar University, Patiala, under the guidance of **Mr. Nitin Narang, Assistant Professor (EIED).**

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

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ABSTRACT

Today the major objective for thermal power generation is to optimize cost as well as emissions because operating at absolute minimum cost can no longer be the only criterion for dispatching thermal power due to increasing concern over the environmental considerations. The multi objective economic-emission dispatch (MOEED) is a conflicting objective function problem which accounts for minimization of both cost and emission.

Modified multi objective particle swarm optimization (MOPSO) technique presents a multi-objective version of the conventional PSO technique and utilizes its efficiency to solve the multi objective optimization problems. In this dissertation work, dynamic search space squeezing strategy based MOPSO has been implemented to solve MOEED optimization problem. By applying modified MOPSO, multiple Pareto-optimal set (non dominated solutions) is produce in a one simulation run. The simulation results also expose the advantage of the modified MOPSO technique in terms of the variety and excellence of the obtained Pareto-optimal solutions. To extract best compromise solution from the set of non-dominated solutions a fuzzy cardinal approach is used. In this dissertation MOEED problems have been solved for six and ten generating unit systems using dynamic search space strategy based modified MOPSO algorithm.

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CHAPTER 1. INTRODUCTION

1.1 OVERVIEW:

Electric power plants utilizing coal as a primary energy source release different types of gases such as sulphur oxides, nitrogen oxides and carbon dioxide into the atmosphere. Excess of these gases in the atmosphere results in as dangerous impact on mankind. The increasing public awareness of the environmental protection has forced the utilities to modify their design or operational strategies to reduce pollution and environmental emissions of the thermal power plants [1]. Multi objective economic emission dispatch (MOEED) is a method to minimize both emission and fuel cost. In recent years, this option has received much attention [2] since it requires only small modification of the basic economic dispatch to include emissions. Several techniques have been reported to handle the MOEED problem [2]. Generally there are three approaches to solve MOEED problem. The first approach treats the emission as a constraint with a permissible limit [2]. The second approach treats the emission as another objective in addition to usual cost objective [3]. Third approach handles both fuel cost and emission simultaneously as competing objectives.

In recent years, multi objective evolutionary algorithm for MOEED problem solution based on the advance version particle swarm optimization (PSO) algorithm, which is called multi-objective PSO (MOPSO) method, has been implemented. Changing conventional single objective PSO to a MOPSO requires redefinition of global and local best individuals to find out a front of optimal solutions. In MOPSO, there is not a single global best, but rather a set of global best. In addition, there may be no single local best entity for each particle of the swarm. The main aim of MOPSO is to reach closer to the set of Pareto-optimal solutions and to get a set of diversified solutions. The reason for success of extending PSO to MOPSO arises because there implementation is simple and it require less parameter tuning.

1.2 MULTI-OBJECTIVE OPTIMIZATION

The multi-objective optimization (MOO) has become elaborated research area during the last few years. It consists of practical optimization problems. The major difficulty of MOO is the simultaneous optimization of the multiple conflicting objectives. In MOO no single solution can be an optimal solution; however, a set of optimal solution is formed. The optimal set of the non-dominated solutions is known as the Pareto-optimal set. The MOO is traditionally based on three approaches, i.e. (i) a priori, (ii) interactive, and (iii) a posteriori. [4] A priori approach uses more information about the preferences of objectives and usually finds one preferred Pareto-optimal solution. An interactive approach uses the preference information progressively during the optimization process. However, it is extremely difficult for the decision maker (DM) to prefer a solution without knowing all the Pareto-optimal solutions [4].Posteriori approach use preference information of each objective and iteratively generate a set of optimal solution. There are two approaches used for solving the MOO problems, i.e., classical search algorithm and evolutionary algorithm (EA). A classical search algorithm uses a point-by-point search method, where one solution in every iteration is evaluated and updated to obtain a superior solution. [4] The ultimate outcome of these methods is a single solution. On the other hand EA uses a population of potential candidate solutions thus; it takes multiple near-optimal solutions in its final population. [4] The multi-point search ability to obtain multiple solutions in a simulation run makes EAs unique in solving MOO problems. There are different types of EAs to solve MOO i.e. genetic algorithm, PSO, ant colony optimization, tabu search, artificial immune system etc.

1.2.1 Principle of Multi-Objective Optimization

Multi-objective optimization problem consists of a number of conflicting objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows: [5]

$$\text{Minimize} \qquad F_i(x) \qquad (i = 1, 2, . . . , N) \tag{1.1}$$

$$\text{Subject to:} \qquad G_j(x) \qquad (j = 1, 2, . . . , M) \tag{1.2}$$

$$H_k(x) \qquad (k = 1, 2, . . . , P)$$

where F_i is the i^{th} objective functions, x is a decision vector that represents a solution, N is the number of objectives and M,P is a number of equality and inequality constraints respectively.

1.2.2 Pareto Optimality Concepts

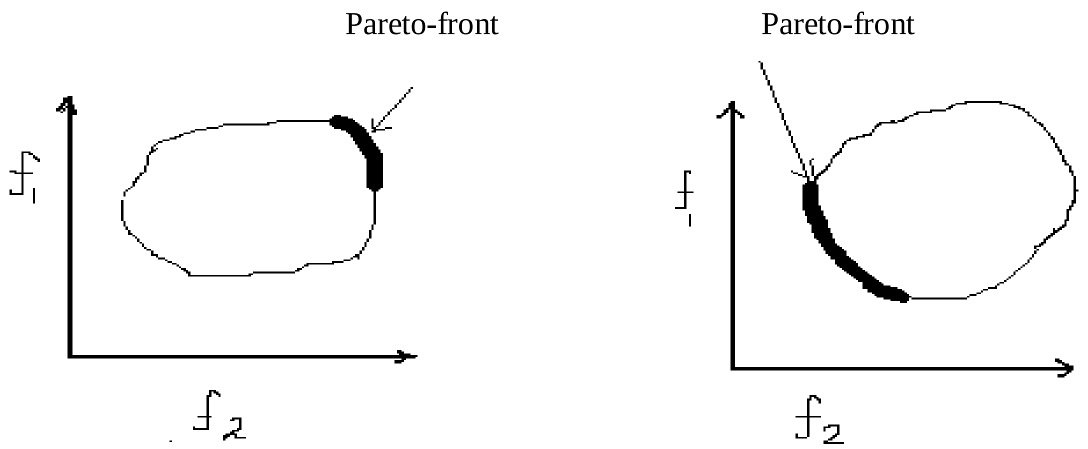
To compare candidate solutions to the multi-objective optimization problems, the concepts of Pareto optimality are commonly used. These concepts were generalized by Vilfredo Pareto [6]. Formally, a decision vector $[\vec{x} = \vec{x_1}, \vec{x_2}, \vec{x_3} \dots, \vec{x_p}]$ is said to Pareto-optimal or Pareto dominate the decision vector $[\vec{y} = \vec{y_1}, \vec{y_2}, \vec{y_3} \dots, \vec{y_p}]$ in a minimization context, if and only if:

1. $\forall i \in \{1, 2, \dots, K\}: \quad f_i(\vec{x}) \leq f_i(\vec{y})$ (1.3)

2. $\exists$ jϵ{1, 2, . . . , K}: $f_j(\vec{x})<f_j(\vec{y})$ (1.4)

where *K* is a number of objective functions.

in the context of MOO, Pareto optimality is used to compare and rank decision vectors: $\vec{x}$dominates $\vec{y}$ in the Pareto sense it means that *f($\vec{x}$)* is better than *f($\vec{y}$)* for all objectives, and there is at least one objective function for which *f($\vec{x}$)* is strictly better than *f($\vec{y}$)*.



Maximize f_1,f_2 **Minimize f_1,f_2**

Fig 1.1 Illustration of Pareto Front for Multi -Objective Optimization Problem. [4]

1.2.3 Dominated and Non-dominated Solutions

For a multi-objective optimization problem, any two solutions x_1 and x_2 can have one of two possibilities: one dominates the other or none dominates the other. In a minimization problem, a solution $x_1$dominates x_2 if the following two conditions are satisfied [4]:

1. $\forall$ iϵ{1, 2, . . . , N_{obj}}: $f_i(x_1)\leq f_i(x_2)$ (1.5)

2. $\exists$ jϵ{1, 2, . . . , N_{obj}}: $f_j(x_1)<f_j(x_2)$ (1.6)

where

N_{obj} : number of objective functions.

If any of the above conditions is violated, the solution x_1 does not dominate the solution x_2. If x_1 dominates the solution x_2, x_1 is called the non-dominated solution. The solutions that are non dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set.

1.2.4 Solution Approaches

There are various approaches which are used to solve the MO problems and are defined as below:-

1.2.4.1 Classical methods

The classical methods convert the multi objective optimization problem (MOOP) into a single objective optimization problem (SOOP) by either aggregating the objective functions or optimizing one objective and consider the other as constraints. The SOOP can be solved by using traditional optimization techniques. Most of these approaches require priori information regarding the importance of the objective or the indication of target optimal values from the DM. Only a single optimal solution is obtained from the classical techniques [4].Various classical techniques is defined as below:

a. Weighted aggregation method

The weighted aggregation (WA) method, convert a set of objectives problem into a single objective problem by pre-multiplying a user-supplied weight to each objective [4]. The WA method requires precise value of the weight for each objective. Conversion of MOOP into SOOP, by using WA can be defined as follows:

$$\text{minimize } Z = \sum_{j=1}^{n} w_j f_j\ (x) \ \text{ with } \ w_j \geq 0 \text{ and} \sum_{j=1}^{n} w_j = 1 \qquad (1.7)$$

where w_j is a weight of j^{th} objective function. Choosing the weights can be problematic if the problem don't have any prior information, then dynamic weighted aggregation (DWA) [7] method is used to solve such type of problems by incrementally changing the weights.

b. Goal programming method

The main idea in goal programming is to find solutions which attain a pre-specified goal for one or more objective functions or minimize the deviation from pre-specified goals. We can formulate the optimization problem by using goal programming method as follows:

$$\text{minimize } Z = \sum_{j=1}^{Q} w_j \left|f_j - G_j\right| \qquad (1.8)$$

where Q is a number of objective functions, G_j represents the goal set by the DM(decision maker) for the j^{th} objective function, and the w_j*'s* now capture the priorities.

c. ε-constraint method

In order to alleviate the difficulties faced by weighted aggregation approach in solving problem having non-convex objective space, the ε-constraint method is used. This method gives the suggestion of reformulating of MOOP by just keeping one objectives and restricting the rest objectives within user specified value [4]. This method is designed to find out the Pareto optimal solutions based on optimization of one objective while treating the other objectives as constraints bound by some allowable range ε_i. The problem is repeatedly solved for different values of ε_i to generate the entire Pareto set [8].

Minimize $f_k(x)$, $x \epsilon \Omega$,

subject to $f_i(x) \leq \varepsilon_i$ $(i = 1, 2, . . . , a)$ $i \neq k$

$$G_j(x) \leq 0 \quad (j = 1, 2, . . . , b) \qquad (1.9)$$

where *b* are number of inequality constraints.

1.2.4.2 Random search techniques

Random search techniques (RST) are move towards direct generation of the Pareto front by simultaneously optimizing the individual objectives, includes genetic algorithms (GA), evolutionary algorithms (EA). Contribution of population-based algorithms raises this technique in recent few years. The main advantage of RST is that it evaluates multiple potential solutions in a single iteration and offer greater flexibility for the decision-maker, mainly when no a priori information is available such as in most real-life MO problems.

a. Non-Pareto-based approaches:

- **Vector-evaluated genetic algorithm (VEGA)**

Vector-evaluated genetic algorithm (VEGA) [9] is a simplest multi objective genetic algorithm having non-Pareto-based approach. If number of objectives (‘I’) have to be handled by VEGA then divide the GA population into ‘I’ equal sub-groups and each sub group is assigned fitness, based on the different objective functions. Now fittest individuals for each objective function are selected. Regular mutation and crossover operations are then performed to obtain the next generation.

b. Pareto-based Approaches:

- **Multi objective genetic algorithm (MOGA)**

A simple and efficient method is MOGA, introduced by Fonceca and Flemin [11]. Which use non dominated solutions as well as maintains diversity in the non dominated solutions. MOGA is different from classical GA in the way the fitness value is assigned to each solution in the population. Rest algorithm is same as GA [4]. Although assigning a different fitness values to a non-dominated front (except the first front), introduce an unwanted bias towards some solution in the search space.

- **Non-dominated sorting genetic algorithm (NSGA)**

Goldberg introduced the idea of NSGA, implemented by Srinivas and Dev [4] in which all non-dominated individuals are assigned the same fitness value and sharing is applied in the decision variable space. The process is repeated for the remainder of the population with a progressively lower fitness value assigned to the non-dominated individuals [12]

- **Strength Pareto evolutionary algorithm (SPEA)**

It uses an external archive to maintain the non-dominated solutions found during the evolution. Candidate solutions are compared to the archive. A MOGA-style fitness assignment is applied: fitness of each member of the current population is computed according to the strengths of all external non-dominated solutions that dominate it. A clustering technique is applied to maintain diversity [13].

1.3 LITERATURE SURVEY

Multi objective PSO is a multi-objective evolutionary algorithm which incorporates Pareto dominance into a PSO algorithm in order to allow the PSO algorithm to handle problems with several objective functions [13]. The main advantages of MOPSO method are: it doesn't require a priori knowledge of the relative importance of the objectives, and there is a set of acceptable trade-off near optimal solutions. MOPSO being an advanced version of the PSO Method has been tried in various applications that is: Xiangwei [14] presented a hybrid Vertical Mutation and self-Adaptation based algorithm that overcome the disadvantages of existing MOPSOs. In this algorithm, ϵ-dominance based archive strategy is adopted. Yang *et al.* [15] introduced a Pareto-optimal solution searching algorithm for finding the global best in MOPSO which can compromise global and local searching based on the process of evolution. Sayyaadi *et al.* [16] implemented the MOO approach in optimization of a benchmark cogeneration system. Objective functions based on the environmental impact evaluation, thermodynamic and economic analysis are obtained and optimized. Mehdipour *et al.* [17]

implemented two evolutionary algorithms that originally search the decision space in a continuous manner including: (1) MOPSO and (2) NSGA-II, considering as the optimization tools to solve two construction project management problems. Wang and Singh [18] discussed an innovative concept for MOEED and an enhanced MOPSO algorithm, used to derive a set of Pareto-optimal solutions. Hazra [19] presented a method for congestion management in transmission grids using cost-efficient generation rescheduling and load shedding. A realistic frequency and voltage dependent modified fast decoupled load flow method is used with multi objective PSO technique to solve this complex problem. Rabbani [20] presented MOPSO for solving project selection problems with simultaneously considering three objectives: maximizing the total benefit, minimizing the total cost, and minimizing the total risk. Ganguly *et al.* [21] presented a guide selection mechanism for the MOPSO, named as the HSG-MOPSO, and its performance on several real-world problem, i.e. multi-objective planning of electrical power distribution systems. Chou [22] optimized the maintenance planning for flexible pavement using a probabilistic reliability-based approach integrated with a MOPSO technique. Carvalho *et al.* [23] discussed the fault-proneness of classes or methods which has been used to devise strategies for reducing testing costs and efforts. Sahoo *et al.* [24] presented a fuzzy-Pareto dominance driven possibilistic model based on planning of electrical distribution systems using MOPSO. Ganguly *et al.* [25] presented a multi-objective planning approach for electrical distribution systems using MOPSO. Vlachogiannis *et al.* [26] extended the PSO methods for solving multi-objective optimization problems. Zhang *et al.* [27] presented a new bare-bones MOPSO to solve the MOEED problem .Wang *et al.* [28] applied MOPSO in stochastic combined heat and power dispatch problem. Wang *et al.* [29] presented a fuzzied MOPSO and implemented to dispatch the electric power considering both economic and environmental issues.

Abido [30] discussed the MOEED problem. To reduce the size of Pareto-optimal set, a clustering technique was used and fuzzy based mechanism is used to extract the best compromise solution. Bouktir *et al.* [31] minimized the total fuel cost of generation and environmental pollution caused by fossil based thermal generating units. Agrawal *et al.* [32] used MOPSO to solve the MOEED problem using fuzzy clustering method. Baguda *et al.* [33] presented MOPSO to reduce the computational time for supporting multimedia application over wireless environment due to high convergence ability .Cai *et al.*[34] presented chaotic MOPSO for MOEED problem and it is compared to conventional MOPSO. El-Gammal *et al.* [35] implemented MOPSO to optimally design a proportional-integral-derivative controller for separately excited DC motor. Gong *et al.* [36] presented a hybrid MOPSO for MOEED problem based on PSO and differential Evolution (DE). Sharaf *et al*. [37] use MOPSO to determine optimal capacitor sizes in a radial distribution system. Chen *et al.* [38] presented the solution for the problem of MOEED using Pareto archived MOPSO satisfying the operational constraint of operation. Coelho [39] used enhanced MOPSO based on Pareto-dominance, to design a brushless DC wheel motor. Kornelakis *et al*. [40] designed a photovoltaic (PV) grid connected systems using MOPSO. It suggests the optimal number of system devices and optimal PV module installation details. Liu *et al*. [41] applied adaptive MOPSO for reactive power optimization and voltage control which was used to reduce the power system loss by adjusting the reactive power variables such as generator voltage, transformer tap setting and other sources of reactive power. Green *et al.* [42] presented MOPSO based state space pruning and also analyzed the impact that transmission line.

There are several literature reviews in the area of minimizing pollution level but still much progress is possible in the area of MOEED. Gent and Lamton [43] have discussed minimum-emission dispatch problem wherein a computer program has been developed for online steam unit dispatch resulting in minimization of NO_X emission employing the newton-raphson convergence for curve fitting. Sullivan [44] also attempted only the minimum pollution dispatch by applying Kun-Tuker condition. Zahavi and Eisenberg [45] suggested an interactive search method based on golden section search technique to solve the MOEED problem. Nanda *et al.* [46] suggested a computational approach by employing an improved complex box method to find minimum emission dispatch problem. Heslin and Hobbs [47] have stated a model for evaluating the cost and employment impacts of effluent dispatching and fuel switching as mean for reducing emissions from power plants. Palanichamy and Srikrishna [48] have stated an algorithm for successful operation of the system to economical and environmental constraints. A price penalty factor has been defined which has blended the emission costs with the normal fuel costs. The quadratic form of objective function has been used because these functions give the optimal result directly. Nanda *et al*. [49] solved this conflicting MOEED problem with the use of linear goal programming technique as well as with non linear goal programming technique. El-Keib *et al.* [50] presented a general formulation of the environmentally constrained economic dispatch problem, using a lagrangian-relaxation-based solution algorithm, which can be easily accommodated in different environmental constraints without major modification. Fan *et al.* [51] presented a solution based on quadratic programming techniques for solving the real-time economic dispatch problems involving emission constraints. Huang *et al.* [52] presented a combined abdicative reasoning network and a technique for order preference by similarity to ideal solution decision approach to solve the MOEED problem and yield the best compromise solution. Singh and Dhillon [53] converted a MOEED problem into a scalar problem. This scalar set optimization problem is then solved different weight pattern to generate non-dominated solutions between the conflicting objectives. Osman, *et al.* [54] presented a epsilon (ϵ)-dominance based multi objective genetic algorithm for MOEED optimization problem. The algorithm maintains a finite-sized archive of non-dominated solution which gets iteratively updated, by using the concept of Epsilon (ϵ) dominance.

Abido [55] presented MOPSO algorithm to solve MOEED problem. Wang and Singh [56] worked on MOEED problem by using a modified MOPSO algorithm for searching out a set of Pareto-optimal solutions. Airashidi and El-Hawary [57] implemented a PSO technique for solving MOEED. Abido [58] used SPEA based approach to handle MOEED. Jeyakumar, *et al.* [59] describes a multi-objective evolutionary programming method to solve the MOEED problem by converting it into single objective optimization problem using weighted sum method. Bhattacharya *et al.* [60] successfully implemented the hybrid differential evolution DE/biogeography-based optimization (BBO) method to solve to solve MOEED problems of thermal generators of power systems. Hota *et al.* [61] employed a modified bacterial foraging algorithm to solve the MOEED problem. A fuzzy based mechanism is employed to extract the best compromise solution over the trade-off curve. The bacterial foraging algorithm appears to be a robust and reliable optimization algorithm as compared to other methods. Guvenc *et al.* [62] formulated gravitational search algorithm as a bi-objective optimization problem to find the optimal solution for MOEED problems. This technique provides a high-quality solution for MOEED problems.

1.4 OBJECTIVES OF THE WORK

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. In order to improve the performance of the solution, the modified multi objective particle swarm optimization algorithm has been implemented to solve multi objective economic emission dispatch problem.

1.5 ORGANIZATION OF THESIS

The dissertation titled as "*Multi Objective Economic Emission Dispatch Using modified Multi Objective Particle Swarm Optimization*" has been summarized in six chapters. The chapter 1 highlights the concise introduction, review of work carried out by various researchers. The chapter 2 explains the multi objective economic emission dispatch chapter 3 describes modified multi objective particle swarm optimization technique used for problem evaluation. The chapter 4 describes the solution approach to multi objective economic dispatch problem using the modified MOPSO. The chapter 5 details the results pertaining to various cases. The chapter 6 summarizes the conclusion and scope for future work.

CHAPTER 2. MULTI OBJECTIVE ECONOMIC EMISSION DISPATCH

2.1 INTRODUCTION

Operating at absolute minimum cost can no longer be the only criterion for dispatching electric power due to increasing concern over the environmental considerations. The generation of electricity from fossil fuel releases several contaminants, such as SO_2, NO_X, CO_2 into the atmosphere. The pressing public demand for clean air and the enforcement of environmental regulations in recent years have changed the dispatch problem with conflicting objectives of minimizing both the fuel cost and the emissions [63].

2.1.1 Conflicting Objective

The multiple objectives of a single decision maker are usually competitive: i.e. the improvement in one of them is associated with deterioration in another. Competitive objectives are sometimes referred to as conflicting objectives. The objectives would conflict to each other, only if there are two or more decision makers who have different objectives and act on the same system or share the same resources. In the MOEED problem, fuel cost and emission are the conflicting objectives. [4]

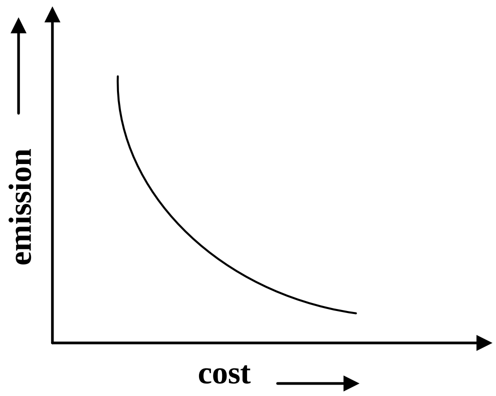


Fig. 2.1 : Graph between Conflicting Objective

2.2 MULTI OBJECTIVE ECONOMIC EMISSION DISPATCH

The multi objective economic emission dispatch involves the simultaneous optimization of fuel cost and emission objectives which are conflicting ones. The problem is formulated as described below:

2.2.1 Problem Objectives

2.2.1.1 Fuel cost objective

The classical economic dispatch problem of finding the optimal combination of power generation, which minimizes the total fuel cost while satisfying the total required demand can be mathematically stated as follows [64]:

the total fuel cost $F(P_G)$ can be expressed as:

$$F(P_G) = \sum_{j=1}^{Ng} a_j + b_j P_{G_j} + c_j P_{G_j}^2 + \left| d_j \sin\left(e_j \left(P_{G_j}^{min} - P_{G_j}\right)\right)\right| \quad (2.1)$$

where Ng is the number of generators, a_j, b_j, and c_j are the cost coefficients of the j^{th} generator and d_j and e_j are the fuel cost coefficients of unit j with valve-point effect and P_{G_j} is the real power output of the j^{th} generator. P_G is the vector of real power outputs of generators and defined as:

$$P_G = \left[P_{G_1}, P_{G_2}, P_{G_3} \dots \dots, P_{GNg}\right] \quad (2.2)$$

2.2.1.2 Emission objective

The minimum emission dispatch optimizes the classical economic dispatch including emission objective, which can be modeled using second order polynomial functions The environmental pollutants such as *SOx* and nitrogen oxides *NOx* caused by fossil-fueled thermal units can be modeled separately. However, for comparison purposes, the total emission $E(P_G)$ of these pollutants can be expressed as[65],[66] :

$$E(P_G) = \sum_{j=1}^{Ng} \left(\alpha_j + \beta_j P_{G_j} + \gamma_j P_{G_j}^2\right) + \zeta_j \exp\left(\lambda_j P_{G_j}\right) \quad (2.3)$$

where α_j ,β_j ,γ_j , ζ_j and λ_j are coefficients of the j^{th} generator emission characteristics.

2.2.1.3 Problem constraints

The optimization problem is bounded by the following constraints:

- **Maximum and minimum limits of power generation**

The power generated, P_{G_j} by each generator is constrained between its minimum and maximum limits, i.e.

$$P_{G_j}^{min} \leq P_{G_j} \leq P_{G_j}^{max} : (j = 1, \ldots\ldots, Ng) \quad (2.4)$$

where

$P_{G_j}^{min}$: minimum power generated

$P_{G_j}^{max}$: maximum power generated.

for stable operation, real power output of each generator is restricted by lower and upper limits.

- **Equality constraints**

Equality constraints in which the total system generation should meet the load demand and system losses as stated below:

$$\sum_{j=1}^{Ng} P_{G_j} - P_D - P_{loss} = 0 \quad (2.5)$$

where:

P_D : total load demand

P_{loss} : transmission losses

the power loss in transmission lines can be calculated by B-coefficients , is defined as [66]:

$$P_{loss} = B_{oo} + \sum_{j=1}^{Ng} B_{jo} P_{G_j} + \sum_{j=1}^{Ng} \sum_{i=1}^{Ng} P_{G_j} B_{ij} P_{G_i} \quad (2.6)$$

2.3 MULTI-OBJECTIVE EED PROBLEM FORMULATION

The MOEED optimization problem [64] is therefore formulated by aggregating the objectives and constraints, the problem can be mathematically formulated as a nonlinear constrained multi objective optimization problem as follows.

$$\text{Minimize } [F(P_G), E(P_G)] \quad (2.7)$$

Subject to:

$$P_{G_j}^{min} \leq P_{G_j} \leq P_{G_j}^{max} \quad (j = 1, 2, \ldots, Ng) \quad (2.8)$$

$$\sum_{j=1}^{Ng} P_{G_j} - P_D - P_{loss} = 0 \quad (2.9)$$

where:

P_D : total load demand

P_{loss} : transmission losses

CHAPTER 3. MODIFIED MULTI OBJECTIVE PARTICLE SWARM OPTIMIZATION

3.1 INTRODUCTION

There are various optimization techniques such as simulated annealing, evolutionary algorithms, neural networks, and ant colony which have been given much attention by many researchers due to their ability to find an almost global optimal solution in economic dispatch problem [68]. One of these modern heuristic optimization techniques is the MOPSO i.e. an advanced version of the PSO. This is a Multi-objective Evolutionary Algorithm (MOEA) which incorporates Pareto dominance into a particle swarm optimization algorithm in order to allow the PSO algorithm to handle problems with several objective functions [69]. Applying PSO to multi-objective optimization very much relies on how to define the local and global best positions. MOPSO keeps tracking the local best for every solution over time. In order to find the global best position for each solution, MOPSO uses an external archive of particles to store all non-inferior solutions. The selection of a particle in the archive is dependent on the compactness of the areas nearby the particle. Further, the archive is updated continuously and its size is controlled by using the clustering technique [4].

Multi-objective optimization method, MOPSO effectively searches for multi-objective optimal solutions i.e., Pareto solution. The main goals of MOPSO are to reach closer to the set of Pareto-optimal solutions for better convergence which can be achieved by selecting a suitable guide for each particle in the particle swarm and get a set of diversified solutions which can be achieved either by proper archiving of the set of non-dominated solutions in successive iterations. There are various archiving techniques for example, crowding distance assignment, dominance and clustering technique [70].

To modify the basic MOPSO the dynamic search space squeezing strategy can be activated which provides the significant improvement in the performance of solution like improvement in the speed of convergence and highly optimal solutions.

3.2 PRINCIPLE OF MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION

Multi objective particle swarm optimization is a population based multi-point search technique that is based on the social behavior of a flock of birds, a fish school, etc. At the start of optimization, for all L particles positions are initialized randomly and velocities are set to zero. The velocity of a particle is updated using its own previous best position $(x^*_{i,j})$ and the best neighborhood particle's position$(x_{i,j}^{**})$. The velocity and position of i^{th} particle in the j^{th} dimension is updated according to the following equation [66]:

$$v_{i,j}(t) = w \times v_{i,j}(t-1) + c_1 r_1 \left(x_{i,j}^{*}(t-1) - x_{i,j}(t-1)\right) + c_2 r_2 (x_{i,j}^{**}(t-1) - x_{i,j}(t-1) \qquad (3.1)$$

$$x_{i,j}(t) = v_{i,j}(t) + x_{i,j}(t-1) \qquad (3.2)$$

where

$v_{i,j}(t)$: velocity of i^{th} particle for the j^{th} dimension at t^{th} iteration.

$v_{i,j}(t-1)$: velocity of i^{th} particle for the j^{th} dimension at $(t\text{-}1)^{th}$ iteration.

$x_{i,j}(t)$: position of i^{th} particle for the j^{th} dimension at$(t)^{th}$ iteration.

$x_{i,j}(t-1)$: position of i^{th} particle for the j^{th} dimension at $(t\text{-}1)^{th}$ iteration.

c_1, c_2 : learning constants

$r_{1,} r_2$: random numbers

w : inertia weight

MOPSO maintains an external archive A_t of non-dominated solutions of the population which is updated after every iteration. This global archive A_t, is empty in the beginning and can store a maximum number of non-dominated solutions which is specified at the start. In case the number of non-dominated solutions exceeds the maximum size of the archive, in any generation, we use clustering to restore the archive size [4]. One distinct feature of this MOPSO is that the individuals here also maintain a personal archive, which we call P_{best} archive with a maximum size. The P_{best} archive contains the most recent non-dominated positions that particle has encountered while searching the space [73]. In each iteration (t), each particle (i) is assigned two guides P_{best} and global best (G_{best}) from its P_{best} archive and G_{best} archive A_t .

3.3 DYNAMIC SEARCH SPACE SQUEEZING STRATEGY

Dynamic search space squeezing strategy is activated to improve the speed of convergence and provides the highly optimal solution. In this case, the search space is dynamically readjusted (i.e. squeezed) based on the relative distance between G_{best} and lower and upper limits of particle (i.e. active power) of i^{th} thermal plant a j^{th} interval denoted by ΔV_{lij} , ΔV_{hij} respectively, which are represented at t^{th} iteration as follows:

$$\Delta V^{t}{}_{lij} = \frac{G_{best}^{t} - P_{ij}^{min}}{P_{ij}^{max} - P_{ij}^{min}} \qquad (3.3)$$

$$\Delta V^{t}{}_{hij} = \frac{P_{ij}^{max} - G_{best}^{t}}{P_{ij}^{max} - P_{ij}^{min}} \tag{3.4}$$

$$\Delta V_{lij} + \Delta V_{hij} = 1 \quad \text{where} \quad (i=1, 2, \ldots, L) \tag{3.5}$$

$$(j=1, 2, \ldots, Ng)$$

The limits of particle (i.e. active power) at t+ 1 iteration can be updated as:

$$P_{ij}^{min,t+1} = P_{ij}^{min} + \left(G_{best}^{t} - P_{ij}^{min}\right) \times \Delta V_{lij}^{t} \tag{3.6}$$

$$P_{ij}^{max,t+1} = P_{ij}^{max} + \left(P_{ij}^{max} - G_{best}^{t}\right) \times \Delta V_{hij}^{t} \tag{3.7}$$

The activation of dynamic search space squeezing process is illustrated in fig. 3.1.

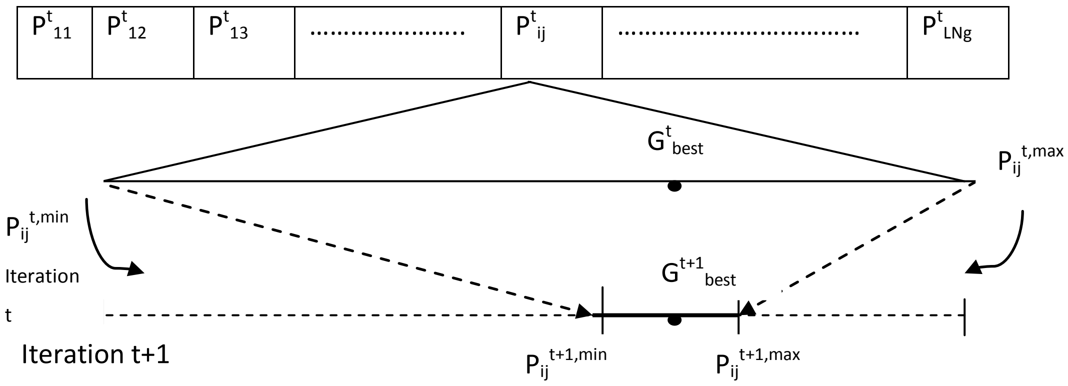


Fig.3.1 Dynamic Search –Space Squeezing Mechanism of Particle during Activation

3.4 MODIFIED MOPSO METHODOLOGY

In the MOPSO algorithm, the population has *L* particles and each particle is an *Ng*-dimensional vector. The computational flow of the MOPSO technique can be described in the following [70], [72]:-

Step 1 (Initialization): Set the time counter t=0 and generate randomly *L* particles, {X_i (0), i=1, 2, . . . ,L}, where $X_i\ (0) = [x_{i,1}\ (0), x_{i,2}(0), \ldots x_{i,Ng}\ (0)]$. $x_{i,j}\,(0)$ is generated by randomly selecting a value with uniform probability over the j^{th} optimized parameter search space $[x_j^{min}, x_j^{max}]$ where (j= 1,2,. . . , Ng). Similarly, generate randomly initial velocities of all particles, $\{V_i(0)\}$, where $V_i(0)=[v_{i,1}(0), \ldots, v_{i,Ng}(0)]$. $v_{i,j}(0)$ is generated by randomly selecting a value with uniform probability over the j^{th} dimension, $[v_j^{min}, v_j^{max}]$ can be calculated as

$$V_j^{max} = .01 * x_j^{max} \tag{3.8}$$

$$V_j^{min} = -.01 * x_j^{max} \tag{3.9}$$

where

V_j^{max} : maximum velocity in the j^{th} dimension

V_j^{min} : minimum velocity in the j^{th} dimension

Step 2 (Objective function evaluation): Each particle in the initial population is evaluated using the objective functions. For each particle, set $S_i^*(0) = \{X_i(0)\}$ and the local best $X_i^*(0) = X_i(0)$. Where $S_i^*(0)$ is a non dominated local set and $X_i^*(0)$ is local best. Search for the non dominated solutions and form the global set $S^{**}(0)$. Set the external set equal to $S^{**}(0)$ and find the global best.

Step 3 (Time updating): Update the time counter t=t+1.

Step 4 (Weight updating): Update the inertia weight.

Step 5 (Velocity updating): Using the local best $X_i^*(t)$ and the global best $X_i^{**}(t)$ of each particle, the i^{th} particle velocity in the j^{th} dimension is updated according to equation (3.1).

Step 6 (Position updating): Based on the updated velocities, each particle changes its position according to the equation (3.2).

Step 7 (Objective function evaluation): Evaluate the objective functions as discussed in step 2.

Step 8 (Non- dominated local set expanding and updating): The updated position of the i^{th} particle is added to $S_i^*(t)$. The dominated solutions in $S_i^*(t)$ will be truncated and the set will be updated accordingly. If the size of $S_i^*(t)$ exceeds a pre specified value, the hierarchical clustering algorithm will be invoked to reduce the size to its maximum limit [71].

Step 9 (Non dominated global set expending and updating): The union of all non dominated local sets is formed and the non dominated solutions out of this union are members in the non dominated global set $S_i^*(t)$. The size of the set will be reduced by hierarchical clustering algorithm if it exceeds a pre specified value [71].

Step 10 (External set updating): The external Pareto-optimal set is updated as follows. Copy the members of $S^{**}(t)$ to the external Pareto set. Search the external Pareto set for the non dominated individuals and remove all dominated solutions from the set. If the number of the individuals externally stored in the Pareto set exceeds the maximum size, reduce the set by means of clustering [71].

Step 11 (Local best and global best updating): Find the local best and global best for each particle.

Step 12 (Apply dynamic search space squeezing strategy): Apply dynamic search space squeezing strategy to contract the maximum and minimum limits of particle.

Step 13 (Stopping criteria): If the number of iterations exceeds the maximum then stop, else go to step 3.

Step14 (Find best compromise solution):

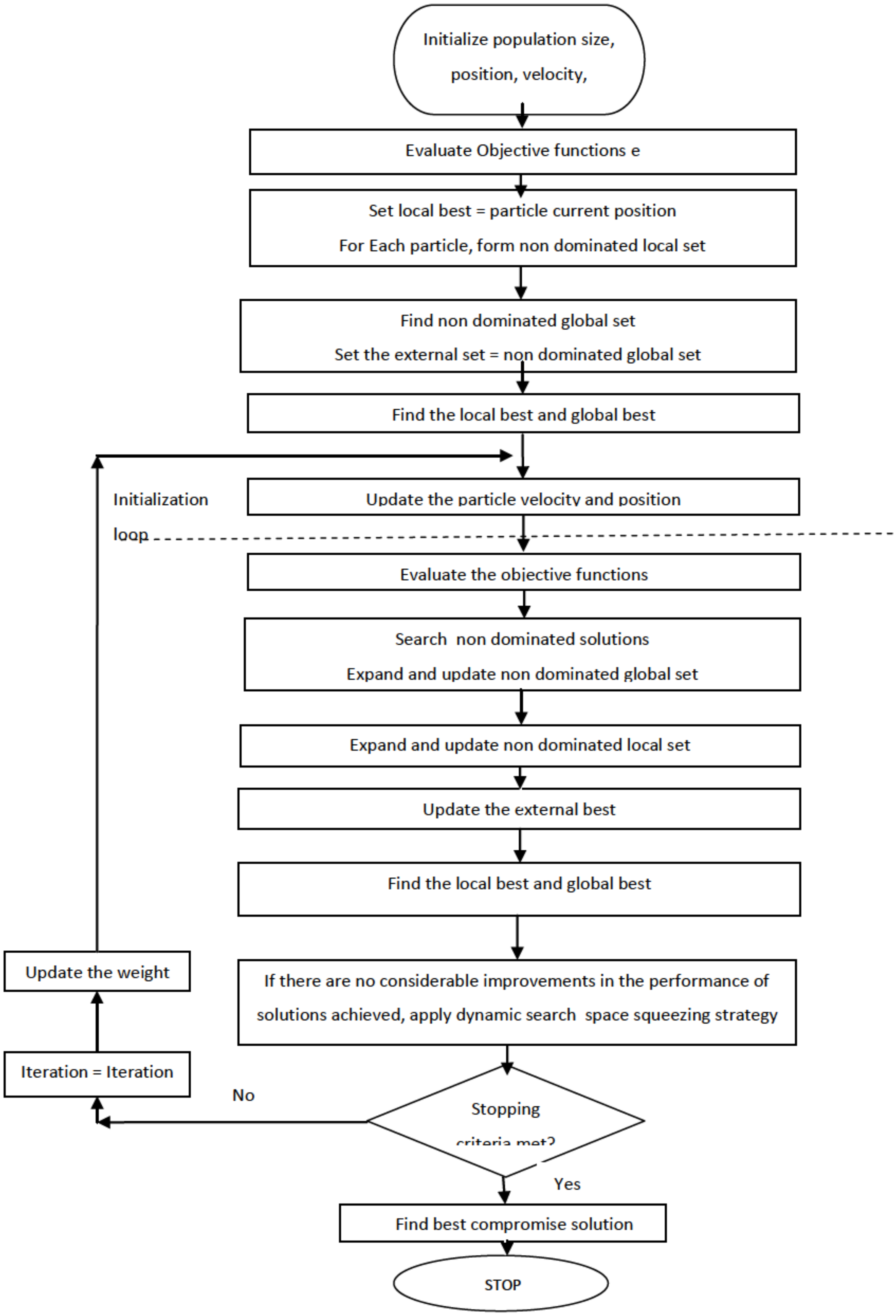
Upon having the Pareto-optimal set of non dominated solution, this approach presents one solution to the decision maker as the best compromise solution. Due to imprecise nature of the decision maker's judgment, each objective function of the *i^th^* solution is represented by a membership function μ_i defined as [6].

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{min} \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} \le F_i \le F_i^{max} \\ 0 & F_i \ge F_i^{max} \end{cases} \qquad (3.10)$$

for each non dominated solution *k*, the normalized membership function μ_k is calculated as:

$$\mu_k = \frac{\sum_{i=1}^{Nd} \mu_i^k}{\sum_{k=1}^{K} \sum_{i=1}^{Nd} \mu_i^k} \qquad (i = 1, 2, . . ., Nd), (k = 1, 2, . . ., K) \qquad (3.11)$$

where *Nd* is the number of objective functions. *K* is the number of non dominated solutions .The best compromise solution is the one having the maximum of μ_{k}.



Flowchart of Modified MOPSO

CHAPTER 4. MULTI OBJECTIVE ECONOMIC EMISSION DISPATCH USING MODIFIED MOPSO

4.1 PROBLEM FORMULATION

The main objective of MOEED is to minimize fuel consumption and to maintain emissions. Here MOPSO algorithm has been implemented for optimization application to solve MOEED. The MOPSO algorithm is used by searching, active power generation 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 [72]. The MOEED problem is formulated by using the principle of multi objective optimization.

$$\text{Minimize } [F\ (P_G), E\ (P_G)] \tag{4.1}$$

subject to:

$$P_{Gj}^{min} \leq P_{G_j} \leq P_{G_j}^{max} \qquad (j = 1, 2, \ldots, Ng) \tag{4.2}$$

$$\sum_{j=1}^{Ng} P_{G_j} - P_D - P_{loss} = 0 \tag{4.3}$$

In optimization problem, any two solutions let us assume, P_{G1} and P_{G2} can have one of two possibilities: one dominates the other or none dominates the other. In this minimization problem, a solution P_{G1}dominates P_{G1} if the following two conditions are satisfied:

$$F(P_{G_1}) \leq F(P_{G_2}) \text{ and} E(P_{G_1}) \leq E(P_{G_2}) \tag{4.4}$$

and for at least one solution

$$F(P_{G_1}) < F(P_{G_2}) \text{ and } E(P_{G_1}) < E(P_{G_2}) \tag{4.5}$$

If any of the above conditions is violated, the solution P_{G1} does not dominate the solution P_{G2}. If P_{G1} dominates the solutionP_{G2}, P_{G1} is called the non-dominated solution. The solutions those are non dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set. The objective functions $F(P_G)$, $E(P_G)$, P_{loss} are defined in equation (4.6) ,(4.8) ,(4.9) respectively as below:

$$F(P_G) = \sum_{j=1}^{Ng} a_j + b_j P_{G_j} + c_j P_{G_j}^2 + \left| d_j \sin\left(e_j\left(P_j^{min} - P_j\right)\right)\right| \quad (4.6)$$

where :

- Ng : is the number of generators
- a_j, b_j, c_j :cost coefficients of the j^{th} generator
- e_j, f_j : fuel cost coefficients of unit j with valve-point effect.
- P_{Gj} : real power output of the j^{th} generator.

P_G is the vector of real power outputs of generators and defined as

$$P_G = \left[P_{G_1}, P_{G_2}, . . . , P_{G_{Ng}}\right] \quad (4.7)$$

$$E(P_G) = \sum_{j=1}^{Ng} \left(\propto_j + \beta_j P_{Gj} + \gamma_j P_{G_j}^2\right) + \zeta_j \exp\left(\lambda_j P_{G_j}\right) \quad (4.8)$$

where :

- $\propto_j$,β_j , γ_j , ζ_j and λ_j : emission coefficients of the j^{th} generator .
- P_{Gj} : real power output of the j^{th} generator.

$$P_{loss} = B_{oo} + \sum_{j=1}^{Ng} B_{jo} P_{gj} + \sum_{j=1}^{Ng}\sum_{i=1}^{Ng} P_{gj} B_{ij} P_{gi} \quad (4.9)$$

4.1.1 Representation of Swarm

The decision variables for the MOEED 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. The complete swarm is represented as below:

$$\text{Swarm} = \begin{vmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1Ng} \\ P_{21} & P_{22} & P_{23} & \cdots & P_{2Ng} \\ \vdots & \vdots & & & \\ P_{L1} & P_{L2} & P_{L3} & \cdots & P_{LNg} \end{vmatrix}$$

where

Ng: number of generating units

L : number of particle in the swarm

4.1.2 Initialization of the Swarm

The elements of swarm are the combination of power outputs of the generating units, which are chosen randomly by a random number. So each element of the swarm matrix is initialized randomly within the real power operating limits by using the formula as given below:

$$P_{ij} = P_j^{min} + rand()(P_j^{max} - P_j^{min}) \quad (4.10)$$

$$P_j^{min} \leq P_{ij} \leq P_j^{max}) \quad (i=1, 2, ..., L) \;, (j=1, 2, ..., Ng) \quad (4.11)$$

where rand() is uniform random number ranging over [0,1]. The velocities of the particles are initialized randomly according to the following equation:

$$V_{ij} = V_j^{min} + rand()(V_j^{max} - V_j^{min}) \quad (4.12)$$

$$V_j^{min} \leq V_{ij} \leq V_j^{max} \quad (i=1, 2, ..., L) \;, (j=1, 2, ..., Ng) \quad (4.13)$$

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:

$$V_j^{max} = .01\, P_j^{max} \quad (4.14)$$

$$V_j^{min} = -.01 P_j^{max} \quad (4.15)$$

4.1.3 Evaluation of Objective Functions

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

$$\text{Error} = \sum_{j=1}^{Ng} P_{ij} - P_D - P_{loss} \quad (i = 1, 2, ..., L) \quad (4.16)$$

where

P_D : total load demand

P_{loss} : transmission losses.

The error as calculated in Eq.(4.17) is now introduced in objective functions Eq.(4.1), Eq.(4.3) changed to the following generalized form:

$$F' = F(P_{ij}) + R \times (Error)^2 \qquad (i=1, 2, ..., L) \ , (j=1, 2, ..., Ng) \qquad (4.17)$$

$$E' = E(P_{ij}) + R \times (Error)^2 \qquad (4.18)$$

where *R* is the penalty factor.

4.1.4 Initialization of Non Dominated Local Set S_i*(0) and Global Set S**(0):

Initially the set after evaluation of objective functions is a non dominated local set. Non-dominated global set from a given set of solutions is similar in principle to finding the minimum of a set of real numbers. There are various approach to find out the non-dominated solutions such as naive and slow approach, continuously updated approach and Kung *et al.* efficient method. [4]

4.1.5 Initialization of Local Best, P*$_i$ (0), and Global Best, Pi**(0):

The global and local best individuals are selected as follows: The individual distances between members in non dominated local set of the i^{th} particle, $S^*_i(0)$, and members in non dominated global set, *S**(0)*, are measured in the objective space. If $P_i*(0)$ and $P_k**(0)$ are the members of $S^*_i(0)$ and *S**(0)* respectively that give the minimum distance, are selected as the local best and the global best of the i^{th} particle respectively. The distance between local best set members and global best set members is calculated as:

$$\text{DISTANCE} = \sum_{j=1}^{d} \left(\frac{f_j(P_i^*) - f_j(P_r^{**})}{\max\left(f_j(P^{**}) - \min\left(f_j(P^{**})\right)\right)} \right)^2 \qquad (i = 1,2, \ldots\ldots L) \qquad (4.19)$$

where

r = maximum number of members in global best set.

i = maximum number of members in local best set.

d = number of objective functions.

4.1.6 Velocity and Real Power Updating

Using the local best $P_i^*(t)$ and the global best $G_{best}(t)$ of each particle, (i=1, 2, . . . , L.) The i^{th} particle velocity and position in the j^{th} (j=1, 2, . . ., Ng) dimension is updated according to the equation (3.1),(3.2) respectively. If power violates its limits in any dimension, set it at the proper limit by fixing them either lower or upper limit that is described as below:

$$P_{ij} = \begin{cases} P_j^{min} & P_{ij} < P_j^{min} \\ P_{ij} & P_j^{min} \leq P_{ij} \leq P_j^{max} \\ P_j^{max} & P_{ij} > P_j^{max} \end{cases} \quad (4.20)$$

4.1.7 Objective Function Evaluation

Evaluate the objective functions $F(P_{i,j})$, $E(P_{i,j})$ in MOEED problem by using updated real power.

4.1.8 Non Dominated Local Set Expanding and Updating

The updated position of the i^{th} objective functions is added to $S_i^*(t)$. The dominated solutions in $S_i^*(t)$ will be truncated and the set will be updated accordingly. If the size of $S_i^*(t)$ exceeds a pre specified value, the clustering algorithm [4] will be used to reduce the size to its maximum limit.

4.1.9 Non Dominated Global Set Expanding and Updating

The union of all non dominated local sets is formed and the non dominated solutions out of this union are members in the non dominated global set $S^{**}(t)$. The size of this set will be reduced by clustering algorithm if it exceeds a pre specified value.

4.1.10 External Set Updating

The external Pareto-optimal set is updated as follows:

Copy the members of $S^{**}(t)$ to the external Preto set. Search the external Pareto set for the non dominated individuals and remove all dominated solutions from the set. If the number of the individuals externally stored in the Pareto set exceeds the maximum size, reduce the set by means of clustering.

4.1.11 Local Best and Global Best Updating

Find the local best and global best *(G_{best})* for each particle.

4.1.12 Dynamic Search Space Squeezing Strategy

The search space is dynamically readjusted lower and upper limits of particle. The limits of particle (i.e. active power) at t+1 iteration can be updated as:

4.1.13 Stopping Criteria

If the number of iterations exceeds the maximum then stop, else go to step 3. Upon having the Pareto-optimal set of non dominated solution, fuzzy-based mechanism to extract the best compromise solution is imposed to present one solution to the decision maker.

4.1.14 Find Best Compromise Solution:

Upon having the Pareto-optimal set of non dominated solution, fuzzy-based mechanism is used to extract the best compromise solution [70].

4.2 ALGORITHM FOR MOEED PROBLEM :

The algorithm for MOEED problem is defined as below:

1. Read data viz. cost coefficients, emission coefficient, maximum allowed iteration ITMAX, size of population (L), size of archive (Na), the dimension of search space (Ng), P_j^{min}, P_j^{max} , (i=1, 2, . . . , L),(j=1, 2, . . . , Ng).
2. Initialize an array of size (LxNg) of random no.
3. Initialize particle, P_{ij} where P_{ij} is the j^{th} coordinate of i^{th} particle by using equation 4.10.
4. Initialize the velocity of particle, v_{ij} .which shows the velocity of i^{th} particle in j^{th} dimension by using equation (4.12).
5. Initialize swarm S_0.
6. Initialize archive A_0=Φ.
7. Compute objective function *F'*, *E'* by using equations, (4.17) and (4.18).
8. Find out the non-dominated solutions from swarm S_0 and send it into archive A_0.
9. Initialize local best set and global best set.

10. Initialize local best and global best by finding the nearest distance between the personal best set members and global best set members by using the equation (4.19).
11. Increment iteration counter I T=IT+1.
12. Generate the velocity of particle by using Eq. (3.1).
13. Update the swarm S_t.
14. Updating the archive and truncate archive by using clustering technique if the size of archive is greater than pre-specified value(i.e. Na).
15. Get global best and local best.
16. Use Dynamic search space squeezing strategy to change the minimum and maximum limit of particle (i.e. active power), using equation (3.6), (3.7).
17. If the number of iterations exceeds the maximum then stop, else go to step-3(in chapter 3).
18. Compute objective functions F', E' by using the solutions which existed in archive.
19. Compute membership function μ_i from Eq. (3.10).
20. Compute the fuzzy cardinal priority μ_k of the non-dominated solutions from Eq.(3.11).
21. Select the solution that attains the maximum membership μ_k.
22. Stop.

CHAPTER5. RESULT AND DISCUSSION

5.1 INTRODUCTION

The earlier chapters provide the whole information of multi objective economic emission dispatch problem and its formulation using modified multi objective particle swarm optimization. The algorithm of modified MOPSO is presented in chapter 4 and has been implemented for solving MOEED problem. The outcome have been obtained by using modified MOPSO and tested on two test functions. Input data is given in APPENDIX - I, II respectively. MOEED is formulated with objectives of minimizing fuel cost and minimizing emission. The following cases have been studied -Case Study 1: For 6 generating units [62]. Case Study 2: For 10 generating units [74].

5.1.1 Case Study 1: Data for the case study 1 has been referred from [62].The system has six generating units. The cost coefficients and emission coefficients of the system is given in the table (5.1) and table (5.2) respectively. The modified MOPSO has been applied to obtain the results (cost and emission). The power generation corresponding to the obtained result is given in the table (5.3) as:

5.1.1.1 Input data for 6-generating unit:

a. Generation limits and cost coefficients of six generating units

Generation limits and cost coefficients of six generating units are given in the table 5.1.

Table-5.1 Generation limits and cost coefficients of six generating units.

Unit j	P_{Gj}^{min} (MW)	P_{Gj}^{max} (MW)	a_j ($/hr)	b_j ($/MWhr)	c_i ($/(MW)^{2}hr)
1	10	125	0.15247	38.5390	756.9888
2	10	150	0.10587	46.1591	451.3251
3	35	210	0.03546	38.3055	1243.531
4	35	225	0.02803	40.3965	1049.9977
5	125	315	0.01799	38.2704	1356.6592
6	130	325	0.02111	36.3278	1658.5696

b. Generation limits and emission coefficients of six generating units:

Generation limits and emission coefficients of six generating units are given in the table (5.2).

Table 5.2: Generation limits and emission coefficients of six generating units.

Unit (j)	P_{Gj}^{min} (MW)	P_{Gj}^{max} (MW)	α_j (Kg/hr)	β_j (Kg/MWhr)	γ_j (Kg/(MW)^{2}hr)
1	10	125	13.8593	0.3267	0.00419
2	10	150	13.8593	0.3267	0.00419
3	35	210	40.2699	0.54551	0.00683
4	35	225	40.2699	0.54551	0.00683
5	125	315	42.8955	0.51116	0.00461
6	130	325	42.8955	0.51116	0.00461

5.1.1.2 Results for six generating units:-

In case study 1, modified MOPSO has been applied for MOEED for six generating units. The inputs are taken from tables 5.1 and 5.2. Cost and emission of six unit system for power demand (P_D) =1000 MW are 51348.81000 \$/hr and 833.362900 Kg/hr respectively are given in table 5.3.

Table 5.3- Shows generation (P_G), cost, emission of 6-unit system problem for power demand (P_D) = 1000 MW without losses.

Units	Power (MW)
1	97.210690
2	67.510540
3	148.65180
4	173.73290
5	243.59570
6	269.29830
Cost (\$/hr)	51348.810
Emission (Kg/hr)	833.36290

5.1.2 Case Study 2: Data for the case study 2 has been referred from [74].The system has ten generating units. The cost coefficients and emission coefficients of the system is given in the table (5.4) and table (5.5) respectively. The loss coefficients are given in section 'c' .The modified MOPSO has been applied to obtain the results (cost and emission). The power generation corresponding to the obtained result is given in the table (5.6) as:

5.1.2.1 Input data for 10 generating units:-

a. Generation limits and cost coefficients of ten generating units:

Generation limits and cost coefficients of ten generating units are given in the table 5.3.

Table 5.3: Generation limits and cost coefficients of ten generating units.

Unit	P_{Gj}^{min} (MW)	P_{Gj}^{max} (MW)	a_j ($/hr)	b_j ($/MWhr)	c_j ($/(MW)^{2}hr)	d_j ($/hr)	e_j MW^{-1}
1	10	55	0.12951	40.5407	1000.403	33	0.0174
2	20	80	0.10908	39.5804	950.606	25	0.0178
3	47	120	0.12511	36.5104	900.705	32	0.0162
4	20	130	0.12111	39.5104	800.705	30	0.0168
5	50	160	0.15247	38.5390	756.799	30	0.0148
6	70	240	0.10587	46.1592	451.325	20	0.0163
7	60	300	0.03546	38.3055	1243.531	20	0.0152
8	70	340	0.02803	40.3965	1049.998	30	0.0128
9	135	470	0.02111	36.3278	1658.569	60	0.0136
10	150	470	0.01799	38.2704	1356.659	40	0.0141

b. Generation limits and emission coefficients of ten generating units:

Generation limits and emission coefficients of ten generating units are given in the table 5.5.

Table 5.5: Generation limits and emission coefficients of ten generating units .

Unit	P_{Gj}^{min} (MW)	P_{Gj}^{max} (MW)	α_j (kg/hr)	β_j (Kg/MWhr)	γ_j (Kg/(MW)^{2}hr)	ξj (Kg/hr)	λ_j (MW^{-1})
1	10	55	360.0012	-3.9864	0.04702	0.25475	0.01234

2	20	80	350.0056	-3.9524	0.04652	0.25475	0.01234
3	47	120	330.0056	-3.9023	0.04652	0.25163	0.01215
4	20	130	330.0056	-3.9023	0.04652	0.25163	0.01215
5	50	160	13.8593	0.3277	0.00420	0.24970	0.01200
6	70	240	13.8593	0.3277	0.00420	0.24970	0.01290
7	60	300	40.2699	-0.5455	0.00680	0.24800	0.01290
8	70	340	40.2699	-0.5455	0.00680	0.24990	0.01203
9	135	470	42.8955	-0.5112	0.00460	0.25470	0.01234
10	150	470	42.8955	-0.5112	0.00460	0.25470	0.01234

c. B-coefficients for 10 generating units:

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	0.000012	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

5.1.2.2 Results for ten generating units:-

In case study 2, modified MOPSO has been applied for MOEED for 10 generating units. The inputs are taken from tables 5.4, 5.5 and section 'c' .Cost, emission and losses of 10-unit system for power demand (P_D) =2000 MW are 113466.50 \$/hr,4114.230Kg/hr and 80.818380MW respectively as given in the table 5.6.

Table 5.6 shows generation (P_G), cost, emission, losses for ten-unit system problem for power demand (P_D) = 2000 MW, by using modified MOPSO.

Units	Power (MW)
1	54.97692

2	75.519490
3	87.805580
4	83.366030
5	139.51390
6	168.94480
7	289.46100
8	315.57570
9	434.62510
10	433.95480
Cost $/hr	113466.50
Emission Kg/hr	4114.2300
Losses (MW)	80.818380

CHAPTER 6. CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION:

Modified multi objective particle swarm optimization is a evolutionary algorithm. It evolves a multi-objective version of the conventional PSO technique to utilize its efficiency in solving the multi objective optimization problems. Dynamic search space squeezing strategy based MOPSO has been simulated in this dissertation work to solve MOEED optimization problem. By applying MOPSO multiple Pareto-optimal set (non- dominated solutions) are produced in one simulation run. Then fuzzy cardinal approach has been used to extract best compromise solution from the Pareto-optimal set. In this dissertation, MOEED problems have been solved for six and ten generating unit systems using dynamic search space strategy based modified MOPSO algorithm.

6.2 SCOPE FOR FUTURE WORK

The scope of work of MOPSO is documented as:

- Modified multi objective particle swarm optimization (MOPSO) algorithm can be implemented in real world problem.
- The problem can be extended by incorporating more than two objectives.

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