COMBINED ECONOMIC AND EMISSION DISPATCH USING ARTIFICIAL IMMUNE SYSTEM

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CERTIFICATE

I hereby certify that the work which is being presented in the dissertation entitled, **"Combined Economic and Emission Dispatch using Artificial Immune System"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in Power Systems and Electric Drives submitted in Electrical and Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr. Sanjay K. Jain, Associate Professor, EIED.

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

The optimal economic dispatch plays an important role in power system optimization. Traditionally, the only importance was given to the minimization of cost of power generation. Nowadays, due to concern of environment by the emission of various gases such as NO_x, SO_2 and CO_2 from the fossil fuels; the consideration of emission has become important. Initially, the emission has been treated as an inequality constraint in the emission dispatch. However, due to conflicting nature of economy and emission objectives, problem of combined economic and emission dispatch is being treated as problem.

In this work, an optimization approach is presented to solve combined economic and emission dispatch (CEED) problem, a multi-objective optimization problem, by using artificial immune system (AIS). The AIS algorithm with clonal selection mechanism is implemented to solve combined economic and emission dispatch while considering the transmission losses. This problem has been solved using AIS by two approaches namely price penalty factor (PPF) approach and fuzzy decision making (FDM) approach. The effectiveness of the formulations has been tested on two test systems comprising three and six generating units, where the losses are expressed using B-coefficients. The results obtained from AIS are compared with the results reported in literature.

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CHAPTER-1

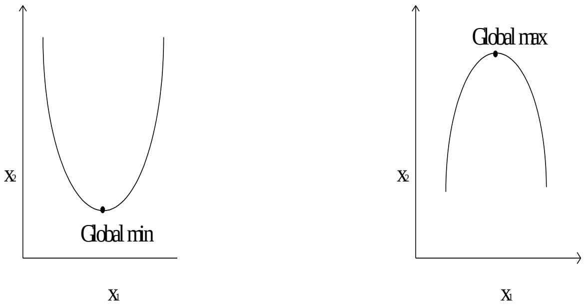
INTRODUCTION

1.1 OVERVIEW

Today in power industry energy management is becoming the most complicated problem. The main objective of electric power utilities is to supply the electricity to the consumers at lowest possible cost with high quality and reliability while considering all violating constrains. This formulates the Economic Dispatch (EDP) problem. The only economic dispatch is not the best in terms of the environment constrains. Because normally the thermal power plants are operated on the basis of minimum fuel cost criteria without considering the harmful impact of emission of gaseous pollutants from fossil fuel power plants on the environment. As large number of thermal plants is employed to satisfy the demand, the quantity of coal burnt is also increasing with increasing demand. This results in increased emission of oxides of sulphur, nitrogen and carbon dioxide polluting the atmosphere. The environmental pollution is one of the major issues not only to the human but also to the entire animal life. So, it has become almost mandatory to take necessary steps to reduce the pollution level below certain limits. Due to increasing concern over the environmental considerations, society demands adequate and secure electricity not only at the cheapest possible price, but also at minimum level of pollution.

Several methods have been proposed for solving this problem. This includes switching to low sulphur content coal, installing post-combustion gas cleaner, and replacement of the aged fuel-burners with cleaner ones [1]. All these conventional methods become very complicated, large time consuming and expensive. On the other hand emission dispatching requires only small modifications to include emission constraints and does not require any additional investment. Therefore, emission dispatch has become an attractive approach for short-term implementation in existing plants. Hence, the main objective of the dispatch problem is to minimize the fuel cost and simultaneously minimize the amount of pollutants of the plants [2]. Thus, a bi-objective optimization problem is dealt. Previously to solve these two problems economic load dispatch and emission dispatch separate mathematically techniques have been used. But present research shows that instead of solving these two problems separately, these can be solved as a combined optimization problem which will give more advantageous results because for these two problems the constraints are same. And this leads to the formulation of combined economic and emission dispatch (CEED).

In single objective optimization problem, there exists only one optimal solution. If the problem is convex for a minimizing type or concave for a maximizing type; the optimal solution can be shown as Fig. 1.1(a) and Fig. 1.1(b) respectively.



(a) Minimization **(b) Maximization**

Fig. 1.1 Representation of optimal solutions for single objective optimization

Due to conflicting objective as in combined economic emission dispatch, a single solution to all objectives does not exist. For this purpose, an effort is made to find a set of trade-off optimal solutions, called pareto-optimal solutions. The set of all feasible non-dominated solutions is called pareto-optimal set. The Fig. 1.2 represents the typical pareto optimal front for min-min type optimization problem as CEED.

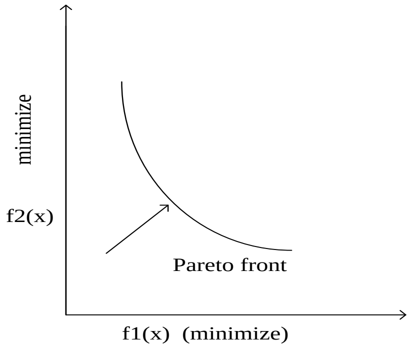


Fig. 1.2 Representation of multi-objective min-min type optimization

Conventional gradient based methods such as Lagarangian multiplier, Newton’s method etc. are not suited for such multi-objective optimization. Further, they are not suited when discontinuous and discrete variables, functions are involved [3-5]. Therefore, various evolutionary techniques such as genetic algorithm (GA) [6], particle swarm optimization (PSO) [7], differential evolution (DE) [8-9], have been used to solve economic load dispatch problems. The multi-objective optimization techniques such as strength pareto evolutionary algorithm (SPEA)[10], multi-objective particle swarm optimization MOPSO [11], evolutionary programming EP [12] and non-dominated sorting genetic algorithm NSGA-II [13] have been used to solve multi-objective environmental/economic dispatch problem.

In this research work, out of various modern techniques, a new optimization approach using artificial immune system (AIS), inspired by the characteristics of immune system (IS), is presented to solve CEED problem. This multi-objective problem has been solved by two approaches namely price penalty factor and fuzzy decision making approach.

The AIS method is based on the biological principle of the body’s immune system. An immunological system has major characteristics that can be used in learning and optimization [14]. Biological models of the natural immune system such as the theories of clonal selection, immune networks and negative selection have provided the inspiration for AIS algorithms. The AIS algorithm has been realized using clonal selection theory. The AIS algorithm with clonal selection mechanism is implemented to obtain CEED considering the losses. The proposed technique is implemented with several cloning, mutation and selection approaches. These approaches are tested and compared in order to determine the strategy for solving the CEED problem.

In order to show the effectiveness of this technique, the proposed approach is applied to two test systems. Numerical results obtained from this approach are compared with different techniques in literature.

1.2 LITERATURE REVIEW

As economic dispatch and emission dispatch are one of today’s most concerned issues for electric power utility. So, in this literature survey various papers and reports which address various aspects of economic dispatch, emission dispatch and CEED problems are presented so far. Artificial immune system which is not limited to engineering field only is also presented to review its various advances.

The optimal power flow procedure consists of methods of utilizing load flow techniques for the purpose of economic dispatch. Carpentier [15] has chronicled the development of optimal power flows from its inception in 1961 and goes on to review several solution methods in existence in 1978. The author has categorized the methods into three families: - classical economic dispatch, general static optimization non-compact methods, and general static optimization compact methods. Classical economic dispatch is limited to real power optimization, taking losses into account, but without security. The non-compact methods include the injections method, the hessian approach, the dommel-timney reduced gradient method and the generalized reduced gradient method. The compact methods are linear and non-linear optimization methods which use several different algorithms.

Chen and Chen [5] have proposed a direct newton–raphson method based to solve the CEED problem with line flow constraints. The Jacobian and B-coefficients are expressed in terms of the generation shift distribution factors.

Nanda *et al.* [4] have presented a classical technique to solve the CEED problem considering line flow constraints. The concept of total cost of generation and pollution level control is introduced for varying degrees of compromise factor decided by the decision maker to reflect the utility function.

Keib *et al*. [5] have described a general formulation of the environmentally constrained economic dispatch (ECED) problem using the Lagrangian relaxation method. The formulation considers NO_x and SO_x constraints. This algorithm can handle both linear and nonlinear environmental constraints.

Shouts *et al.* [16] have introduced an approach for computation of loss coefficients based on method of least squares. The authors have incorporated this method of computing loss coefficients in a classical economic dispatch. The results obtained from this method are compared with load flow techniques.

Along with the classical methods, various other techniques such as successive linear programming, nonlinear programming and successive quadratic programming have been described in literature by different authors [17-18].

Reid and Hasdorff [18] have developed the economic load dispatch problem as a quadratic programming problem. The quadratic programming algorithm does not require penalty factors and the determination of gradient step size which can cause convergence difficulties.

Various evolutionary techniques, such as genetic algorithm (GA) [19], particle swarm optimization (PSO) [20], differential evolution (DE) [21] and artificial bee colony optimization (ABC) [22] have been discussed in the literature to solve economic load dispatch.

NSGA-II is a multi-objective genetic algorithm which is based upon non-dominated sorting scheme. The aim of the multi-objective optimization is to find solutions which are close to pareto-optimal solution. Solutions should be as diverse as possible in the obtained non-dominated front. NSGA-II meets the both of the objectives as given by Deb *et al.* [13].

Purkayastha and Sinha [23] have used NSGA-II algorithm for optimal combined economic and emission load dispatch. NSGA-II is used with adaptive crowding distance called modified NSGA-II. The proposed method is tested on a test case of 40 units for optimum CEED problem.

Horn *et al.* [24] have proposed niched pareto genetic algorithm (NPGA) for solving multi-objective optimization problem. It is based upon tournament selection based pareto dominance principle. In this method, for selecting winner, two individuals and a comparison set are selected at random from the population.

Abido [25] has described the NPGA approach applied in environmental/economic power dispatch optimization problem. This method has diversity preserving mechanism to find widely different pareto-optimal solution. A clustering technique is also implemented to provide the operator with a representative and manageable pareto-optimal set without destroying the characteristics of the trade-off front.

Over past few years, there have been several proposals for extending PSO to multi-objective PSO and these methods are called multi-objective particle swarm optimization (MOPSO). Abido [11] has proposed MOPSO technique by redefining the global best individuals in multi-objective optimization domain. Clustering algorithm is used to manage the size of the pareto-optimal set and fuzzy approach is used to extract the solution between minimum cost and less emission.

Multi-objective differential evolution (MODE) is the advancement of differential evolution. In MODE, a pareto-based approach is used to implement the selection of the individuals. Basu [26] has worked on the MODE algorithm for environmental economic load dispatch problem. The results obtained from the proposed algorithm have been compared with pareto differential evolution and NSGA-II method.

Kar *et al.* [27] have described a multi layer feed-forward artificial neural network (ANN) algorithm to solve CEED problem. The neural network is trained by back propagation method. The objective is to minimize fuel cost and control emission. The author firstly used Lagrange multiplier technique and the obtained result is used to train ANN by back propagation.

Balamurugan and Subramanian [28] have developed a mathematical approach to find the optimal solution of CEED problem. In this bi-objective CEED problem is converted into single objective function by using price penalty factor. The authors have also introduced dynamic programming (DP) technique to solve the CEED problem.

Hamedi [29] has proposed an advanced parallelized synchronous particle swarm optimization (PSPSO) algorithm for finding the optimal combination of power generation units that minimizes the fuel cost and emission. In this algorithm, positions and velocities are updated at the end of each iteration.

Venkatesh *et al*. [30] have developed evolutionary programming techniques for combined economic and emission dispatch with line flow constraints. The bi-objective problem is converted into single objective by using piece penalty factor. In this the authors have used evolutionary computation (EC) methods such as genetic algorithm (GA), micro GA (MGA) and evolutionary programming (EP) to obtain CEED solutions. A nonlinear scaling factor is also introduced in EP to improve the convergence performance.

Artificial immune system (AIS) has been widely used to solve economic load dispatch problem, combined economic emission dispatch, electric load forecasting, fault detection, optimal reactive power flow.

Vanaja *et al.* [31] have proposed AIS based optimization approach to solve the economic load dispatch with valve-point effect. The developed AIS based optimization technique used total cost of generation as the objective function and represented it as the affinity measure.

Behera *et al.* [32] have introduced AIS algorithm used in automatic control system to get the real-time economic dispatch. Artificial immune system algorithm is also termed as the machine learning approach with potential features of random search, hill climbing, statistical sampling, competition and problem reduction, flexibility.

Geetha *et al.* [33] have developed an approach to solve CEED problem based on AIS. The approach utilizes the clonal selection principle and evolutionary approach wherein cloning of antibodies is performed followed by hypermutation. The developed AIS optimization technique uses the total operating cost as the objective function and is represented as the affinity measure.

Aydin *et al.* [34] have introduced an artificial immune inspired fault detection algorithm based on fuzzy clustering and genetic algorithm. Its purpose is to detect broken rotor bar and broken connector faults in induction motors.

Sheng *et al.* [35] have proposed an algorithm for optimizing reactive power using artificial immune ant colony algorithm. This hybrid algorithm uses artificial immune algorithm (AIA) to give pheromone to distribute and makes use of ant colony algorithm (ACA) to give the optimal solution. The improved ACA uses the best and worst ant to update the pheromone trails and pseudorandom proportional rule.

Honorio *et al.* [14] have proposed an evolutionary algorithm based on a cluster and gradient based artificial immune system (CGbAIS) is used to solve optimal power flow problems. In this algorithm, numerical information provided by the electrical power system and a clustering strategy, are used.

1.3 OBJECTIVE OF THE WORK

It has been observed that there are concerns to both the operating cost of the thermal plant and the emission caused by them. For true optimization, both the objectives namely fuel cost and emission must be accounted simultaneously.

The work reported in this dissertation has been carried out with an objective to attempt combined economic and emission dispatch (CEED) as multi-objective optimization problem and its solution using artificial immune system. The work is also carried out with the objective to develop algorithm to implement AIS to solve CEED using known price penalty factor approach represented as CEED-PPF and fuzzy decision making approach represented as CEED-FDM and compare the results obtained from developed algorithms with the results reported in literature.

1.4 ORGANIZATION OF THE DISSERTATION

This report is organized into five chapters. The **Chapter 1** includes the brief overview, literature review, objective of the work and organization of the dissertation. The **Chapter 2** explains the artificial immune system (AIS), theories of artificial immune system and clonal selection based AIS algorithm and flowchart. The **Chapter 3** describes the formulation of economic load dispatch (ELD), emission dispatch, combined economic emission dispatch (CEED), calculation of price penalty factor, representation of fuzzy decision making function for obtaining the best result between emission and fuel cost and realization of clonal selection-based AIS for combined economic and emission dispatch via price penalty factor and fuzzy decision making. The **Chapter 4** details the results pertaining to various cases and comparison of results obtained for various solutions. The **Chapter 5** summarizes the conclusions and the scope of the further work.

CHAPTER-2

ARTIFICIAL IMMUNE SYSTEM (AIS)

2.1 INTRODUCTION

Artificial immune system (AIS) is developed through mathematical and computational modeling of immunology which has wide area of research in the engineering field, abstraction from those models into algorithm design and implementation in context of engineering. The understanding and investigation on natural immune system leads to development of new algorithms inspired by natural immune system, under a new branch of computational intelligence known as artificial immune system (AIS). It has been defined as adaptive system inspired by theoretical immunology and observed immune functions, principles and models and is applied to problem solving [36].

Artificial immune system is a model of natural immune system that can be used for experimentation, explanation and prediction activities. It is based on biological principle human's body immune systems. An immunological system has main four characteristics that can be used in large optimization problems [37]: proliferation, mutation, selection and memory. Proliferation is the process of generating new individuals. Mutation is the capability of searching through the solution space for sub-optimum points. The selection is responsible for eliminating low affinity cells while memory is responsible for storing high- affinity cells from the solution space and using this memory in new problems intending to reduce optimization time.

2.2 BIOLOGICAL INPRETATION OF ARTIFICIAL IMMUNE SYSTEM

The biological interpretation of AIS is well summarized in [36-39]. The natural immune system is a complex and robust system that protects the human body from various foreign invaders. It is an adaptive system that maintains a state of equilibrium among various types of molecules, cells and tissues present in human body. It's vital role is to detect the foreign invaders and act accordingly in order to neutralize their effect. The invading particles or pathogen known as antigen stimulates the immune system. Antigens may originate from within the body or the external environment leading to the production of antibodies.

The immune system is a multilayer system with defense mechanism in several layers. The three main layers are: innate immunity, adaptive immunity and anatomic barrier. These are described as follows:

2.2.1 Innate immunity

Innate immunity is defensive to against any invading pathogen. It is transferred from the mother to the baby during the individuals are born. The innate immune system is not antigen specific and reacts equally well to a variety of organisms. It is ready to mobilize upon the first signs of infection. It does not demonstrate immunological memory. This type of defense system is also called natural immunity. It includes two parts. First is the humoral innate immunity, involves a variety of substances found in the humors or body fluids. These substances interfere with the growth of pathogens or clump them together so that they can be eliminated from the body. The second part is called cellular innate immunity, is carried out by cells called phagocytes that ingest and degrade, or eat pathogens and by so called natural killer cells.

2.2.2 Adaptive immunity

Adaptive immunity also called acquired or specific immunity represents the part of the immune system that is able to specifically recognize and selectively eliminate foreign microorganism and molecules. It works with innate immunity to provide vertebrates with a heightened resistance to microorganisms, parasites and other intruders that could harm them. The adaptive immune system requires some time to react to an invading organism. But it demonstrates immunological memory that remembers that it has encountered an invading organism and reacts more rapidly on subsequent exposure to the same organism.

2.2.3 Anatomic barrier

Anatomical barriers are integral barriers that restrict the entry and colonization of many microbes. Examples include the skin, the mucous membranes and bony encasement. The skin, consisting of the epidermis and the dermis, is dry, acidic and has a temperature lower than 37^{o}C (body temperature). These conditions are not favorable for the growth of bacteria.

2.3 VARIOUS THEORIES FOR ARTIFICIAL IMMUNE SYSTEM

This section describes the introduction about AIS theories. Mainly three forms of algorithm reported in the literature are negative selection theory, clonal selection theory and immune network theory.

2.3.1 Clonal selection theory

The clonal selection principle describes the basic features of an immune response to an antigenic stimulus. It establishes the idea that only those cells that recognize the antigen proliferate, thus being selected against those that do not. This algorithm is inspired by the way in which B-cells lymphocytes adapt in response to antigen encounter. Since the presented work is based upon the clonal selection algorithm, a comprehensive overview of clonal selection theory is given in section [2.4].

2.3.2 Negative selection theory

As well as responding to antigen coming from external invaders, lymphocytes can react to material coming from the host's own cells. If this leads to a full immune response, this can result in damage to the host organism (this is called auto-immunity). Negative selection is a mechanism employed to protect the body against self-reactive lymphocytes. It provides tolerance for self-cells. It detects unknown antigens while not reacting to the self cells. During the generation of T-cells, receptors are made through a pseudo-random genetic rearrangement process. Then, they undergo a censoring process in the thymus, called the negative selection [38]. In this process, only T-cells that do not bind to self-proteins are allowed to leave the thymus. These matured T-cells perform the immunological functions and protect the body against foreign antigens.

2.3.3 Immune network theory

The concept of immune Network theory has been introduced by Jerne (1974) [38], postulates that immune system is an intricate network of cells that recognize one another in the absence of antigens. The immune network maintains an idiotypic network of interconnected B cells for antigen recognition. These cells are interconnected with each other to stabilize the network. Two B cells are connected if the affinities between them exceed a certain threshold, and the strength of the connection depends upon the affinity between them. The formation of such a network is possible by the presence of paratope and idiotope on the each antibody cell. The paratope present on one B-cell is recognized by other B-cells idiotopes so each cell recognizes as well as recognized. In network formation point of view two things are very important: antigen-antibody binding and antibody-antibody binding. This idiotypic network can also be thought of as having cognitive capabilities that makes it similar to a neural network.

2.4 CLONAL SELECTION AS AN EVOLUTIONARY PROCESS

Clonal selection theory is one of the fundamental models used to explain the behavior of the modern immune system that how the immune cells eliminate a foreign antigen. The Clonal selection algorithm (CSA) named CLONALG, proposed by De Castro and Von Zuben [40] is a population based stochastic method used for achieving optimum solution.

The clonal selection process is described in [41]. It is modeled on the natural B-cell mechanism. Only those cells that acknowledge the particular antigens are selected to proliferate and thus go through the affinity maturation process. In the selection stage, B cells with high affinity with respect to an antigen are activated and inspired to proliferate producing a large number of clones. In the maturation process, these clones are mutated by mutation or hypermutation depending upon the affinity and turned into plasma cells which then produce a large number of antibodies. Some of the B cells clones are maturated into memory cells that have the memory of the antigenic pattern for future infections. The clonal selection process, as illustrated in [42] is shown in below Fig. 2.1. The antibodies secreted from the second response would have higher affinity than those of the earlier response.

With AIS based Clonal selection algorithm during the process of optimization, affinity is evaluated using fitness or objective function value while satisfying different constraints. The number of clones generated per antibody is dependent on the affinity or fitness value. Hence more number of clones is generated for the antibodies with larger fitness value and less number of clones is generated for the antibodies with smaller fitness value.

The important features of the clonal selection theory are [43]:

- New cells are copies of their parents (clone), subject to a mutation mechanism.
- Self-reactive cells are eliminated.

- Proliferation and differentiation of mature cells on contact with antigens.
- The persistence of forbidden clones provides resistant to early elimination by self-antigens as the basis of autoimmune diseases.

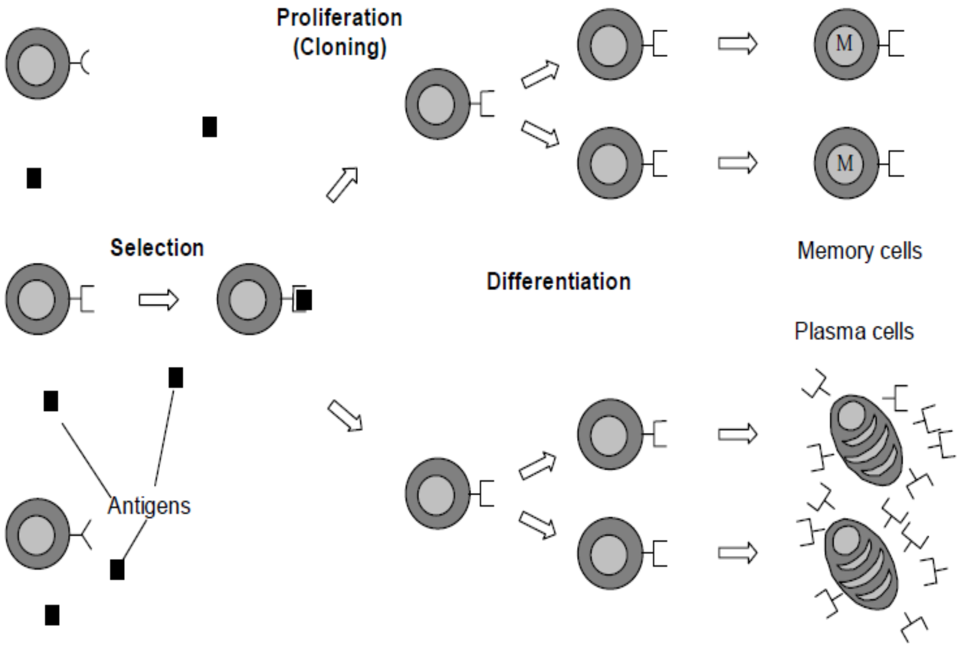


Fig. 2.1 Illustration of clonal selection process

2.4.1 Ag-Ab representation and affinity

The Ag-Ab representation calculates the degree of interaction between antigen and antibody. The affinity between an antigen and an antibody is related to their distance that can be estimated via any distance measure between two strings (or vectors), for example the euclidean distance. In the case of euclidean distance, if the coordinates of an antibody are given by <ab_1, ab_2, …., ab_l> and the coordinates of an antigen are given by <ag_1, ag_2, ..., ag_l>, then the distance (*D*) between them [42] is expressed as equation (2.1).

$$D = \sqrt{\sum_{i=1}^{l} (abi - agi)^2} \qquad (2.1)$$

2.4.2 Computational aspects of clonal selection principle

After discussing the clonal selection theory and the affinity maturation process, the development and implementation of CSA [39] is discussed below. CSA is composed of two set populations: a set of antigens Ag and a set of antibodies Ab. The main immune aspects taken into account to develop the algorithm are:

- Maintenance of a specific memory set.
- Selection and cloning of the most stimulated Ab's
- Death of non stimulated Ab's
- Affinity maturation.
- Reselection of the clones proportionally to their antigenic affinity, generation and maintenance of diversity.

The following list contains the symbols which are used to describe the clonal selection algorithm:

Ab	Available antibody repertoire
$Ab_{\{m\}}$	Memory antibody repertoire
$Ab_{\{r\}}$	Remaining antibody repertoire
$Ag_{\{M\}}$	Population of antigens to be recognized
f_j	Vector containing the affinity of all antibodies with relation to the antigen Ag_j
$Ab^j_{\{n\}}$	n antibodies from Ab with the highest affinities to Ag_j
C^j	Population of clones generated from $Ab^j_{\{n\}}$
C^{j*}	population C^j after the affinity maturation process
$Ab_{\{d\}}$	Set of d new molecules that will replace d low affinity antibodies from $Ab_{\{r\}}$
Ab^{j*}	Candidate, from C^{j*}, to enter the pool of memory antibodies

2.4.3 AIS Algorithm based on clonal selection

The clonal selection algorithm illustrated in Fig. 2.2 can be implemented in the following steps [39]:

Step 1: Select an antigen randomly from population of antigens to be recognized $Ag_{\{M\}}$ and present it to all antibodies in the repertoire Ab.

Step 2: Determine the affinity of the chosen antigen to all the antibodies in Ab and put it in vector f_j.

Step 3: The higher affinity antibodies to the chosen antigen are selected from the Ab to form a new set of population of high affinity antibodies ($Ab^j_{\{n\}}$).

Step 4: These selected antibodies are now proliferated independently to generate another repertoire C^j of clones. The generation of clones is proportional to affinity value.

Step 5: The repertoire C^j is gone through an affinity maturation process to generate another repertoire C^{j*} of clones.

Step 6: Determine the affinity of the matured clones C^{j*} in relation to the antigen and put it in vector f_j^*.

Step 7: From C^{j*} the antibody with highest affinity with respect to chosen antigen is re-selected to enter the set of memory antibodies $Ab_{\{m\}}$. If there already exists an antibody in $Ab_{\{m\}}$ which affinity is lower, than it is replaced by the new one.

Step 8: The d lowest affinity anticbodies from $Ab_{\{r\}}$ are replaced by new individuals.

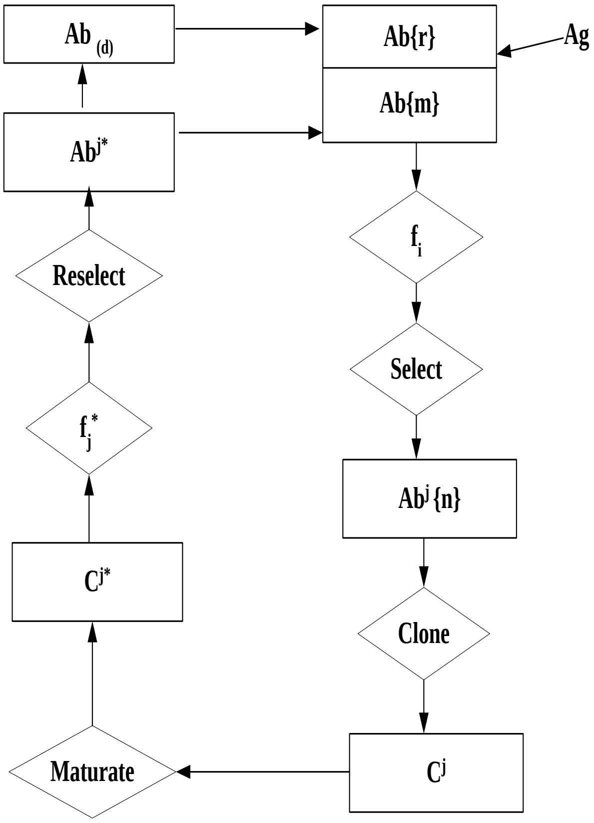


Fig. 2.2 Flowchart of clonal selection process

CHAPTER-3

COMBINED ECONOMIC AND EMISSON DISPATCH USING AIS

3.1 INRODUCTION

Most of the real world problems are generally characterized by the presence of many conflicting objectives such as cost, capacity performance, system efficiency and reliability. Therefore, it is necessary to consider all the conflicting criteria's simultaneously while selecting the most suitable solution. In such cases, it is necessary to look at the problem as a multi-objective optimization problem (MOOP).

The combined economic and emission dispatch (CEED) problem is a multi-objective optimization problem. The main purpose of CEED is to allocate generation levels to the generating units, so that the system is able to meet the power demand at minimum cost and minimum emission level simultaneously while satisfying the constraints. The AIS algorithm with clonal selection mechanism is implemented to obtain optimal economic and emission dispatch considering the losses. This problem has been solved by two approaches namely price penalty factor and fuzzy decision making approach.

3.2 PROBLEM FORMULATION

Economic dispatch, emission dispatch or combined economic emission dispatch (CEED) are solved to find the values of P_g for generating units. The formulation of these problems is described below:

3.2.1 Economic dispatch

Economic dispatch is defined as the process of allocating generation levels to the generating units, so that the system is able to meet the power demand at minimum cost. Economic dispatch problem can be formulated as follows:

$$Minimize\ \ FC = \sum_{i=1}^{NG} F_i\left(P_{gi}\right) \tag{3.1}$$

$$F_i\left(P_{gi}\right) = a_i + b_i P_{gi} + c_i P_{gi}^2 \tag{3.2}$$

where

$F_i(P_{gi})$	is the operating fuel cost of the ith unit in Rs. /hr
P_{gi}	is the decision variable, i.e. real power generation corresponding to the ith generating unit
NG	is the number of generating units
FC	is the total fuel cost
a_i, b_i, c_i	are the cost coefficients of the ith generating unit.

Subjected to:

(i) Equality constraint

The total generation must be able to meet total load demand and total transmission losses.

$$\sum_{i=1}^{NG} P_{gi} = P_D + P_L \tag{3.3}$$

P_D represents the total load demand and P_L represents the total transmission loss.The transmission losses can be calculated by using B-coefficients, frequently known as kron’s loss formula given as:

$$P_L = B_{oo} + \sum_{i=1}^{NG} B_{io} P_{gi} + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gj} \tag{3.4}$$

where

P_{gi} and P_{gj} are the real power generation at the i^th^ and j^th^ buses respectively and B_{oo}, B_{io}, B_{ij} are the loss coefficients.

(ii) State variable

The power generation (P_{gi}) of each generating unit is taken as state variable which is within the minimum and maximum generating limits.

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \tag{3.5}$$

where

P_{gi}^{min} and P_{gi}^{max} are the minimum and maximum power output of the ith generating unit respectively.

3.2.2 Emission dispatch

The main objective of the emission dispatch is to maintain the pollution within environment license irrespective of the type of fuel. The minimum emission dispatch problem can be formulated as follows:

$$Minimize\ E_T = \sum_{i=1}^{NG} E_i(P_{gi}) \tag{3.6}$$

$$E_i(P_{gi}) = d_i + e_i P_{gi} + f_i P_{gi}^2 \tag{3.7}$$

Where

$E_i(P_{gi})$ is the emission of the ith unit in Kg/hr

d_i, e_i, f_i are emission coefficients of the ith unit

E_T is the total emission level (Kg/hr)

For emission dispatch, equality constraints and limits on state variables can be expressed by equation (3.3) and (3.5) respectively.

3.2.3 Combined economic and emission dispatch (CEED)

The main objective of the combined economic and emission dispatch (CEED) problem is to optimize the fuel cost and emission simultaneously. So, the CEED problem can be formulated as:

$$Minimize\ TC(FC, E_T) \tag{3.8}$$

where

FC is the total fuel cost in Rs/hr

E_T is the total emission in Kg/hr

For the CEED, equality constraints and limits on state variables can be expressed by equation (3.3) and (3.5) respectively.

3.3 PRICE PENALTY FACTOR

To find the best optimal solution to have minimum fuel cost and emission, the multi-objective problem is converted into single objective by incorporating the price penalty factor k. The price penalty factor can be evaluated as follows [33]:

1. Calculate the fuel cost for each generating unit corresponding to the maximum generating power limit.

$$F_i\left(P_{gi}^{max}\right) = a_i + b_i P_{gi}^{max} + c_i P_{gi}^{max2}\ \text{Rs/hr} \tag{3.9}$$

2. Calculate the emission level for each generating unit corresponding to the maximum generating power limit.

$$E_i\left(P_{gi}^{max}\right) = d_i + e_i P_{gi}^{max} + f_i P_{gi}^{max2}\ \text{Kg/hr} \tag{3.10}$$

3. The price penalty factor for each unit as:

$$k_i = \frac{F_i\left(P_{gi}^{max}\right) = a_i + b_i P_{gi}^{max} + c_i P_{gi}^{max2}}{E_i\left(P_{gi}^{max}\right) = d_i + e_i P_{gi}^{max} + f_i P_{gi}^{max2}} \text{ton/h} \tag{3.11}$$

4. Arrange k_i in increasing order for i=1, 2…….NG generating units.

5. Add maximum generating capacity i.e. P_{gi}^{max} of each unit once at time, starting from the smallest k_i untill it does not exceed the load demand i.e. $\sum_{i=1}^{NG} P_{gi}^{max} \geq P_D$.

6. During this process the value of k_i corresponding to that unit is the price penalty factor k in Rs/Kg.

So the problem of CEED can also be formulated as:

$$Minimize\ TC = FC + (k \times E_T) \tag{3.12}$$

$$Or\ Minimize\ TC = FC + EC \tag{3.13}$$

$$Or\ Minimize\ TC = \sum_{i=1}^{NG}[(a_i + kd_i) + (b_i + ke_i)P_i + (c_i + kf_i)P_i^2] \tag{3.14}$$

where $EC = k \times E_T$ is the emission cost in Rs/hr

A trade-off between the fuel cost and emission cost is made by introducing the weighting factor as shown below:

$$\text{Minimize } TC = w_i \times FC + w_2 \times k \times E_T \tag{3.15}$$

where $w_1$and $w_2$are the weighting factors and

If $w_1 = 1$ and $w_2 = 0$ then the problem is of classical economic load dispatch.

If $w_1 = 0$ and $w_2 = 1$ then the problem is of classical emission dispatch.

If $w_1 = 1$ and $w_2 = 1$ then the problem is of combined economic and emission dispatch

If different values are assigned to w_1 and w_2 between 0 and 1 then a compromise is made between the two problems.

3.4 FUZZY-DECISION MAKING

The decision regarding the best solution is made from the following objective function [44] as:

$$Objective\ maximize\ \mu = max[min\{\mu(F_i), \mu(E_i)\}] \tag{3.16}$$

Where the fuzzy membership functions $\mu(F_i), \mu(E_i)$ are calculated for both fuel cost and emission as follows:

$$\mu(F_i) = \left[\frac{F^{max} - F_i}{F^{max} - F^{min}}\right] \quad F^{max} \leq F_i \leq F^{min} \tag{3.17}$$

$$\mu(E_i) = \left[\frac{E^{max} - E_i}{E^{max} - E^{min}}\right] \quad E^{max} \leq E_i \leq E^{min} \tag{3.18}$$

$$i = 1,2 \ldots \ldots .., POP$$

where

$\mu(F_i)$ and $\mu(E_i)$ are the fuzzy membership functions corresponding to the fuel cost and emission respectively

F^{max} and F^{min} are maximum and minimum values of fuel cost in the population POP in a given iteration

E^{max} and E^{min} are maximum and minimum values emission in the population POP in a given iteration

F_i and E_i are the fuel cost and emission corresponding to the ith solution in the population POP

3.5 REALIZING CEED USING AIS VIA PRICE PENALTY FACTOR

To implement clonal selection algorithm to combine economic and emission dispatch (CEED) problem following assumptions are made [43]:

- There is no explicit antigen to be recognized, but an objective function is to be optimized. Therefore the affinity of an antibody refers to the evaluation of the objective function.
- All antibodies are to be selected for cloning.
- The number clones generated by the antibodies are equal. However, it is investigated that the number of clones generated varies according to the affinity.

Algorithm

The stepwise procedure of AIS for the optimization of generation cost and emission [32] based upon price penalty factor approach is listed below. The same has also been depicted in flowchart shown in Fig. (3.1).

Step 1: Read data namely cost coefficients a_i, b_i, c_i, emission coefficients d_i, e_i, f_i and B-coefficients, B_{ij} (i=1,2, ……….., NG; j= 1,2, …………, NG), convergence tolerance, P_{gi}^{min} ,P_{gi}^{max}, number of iterations ITMAX, String length l and population size POP.

Step 2: Generate and decode population of random binary strings to calculate the generating power of each unit except slack bus within the limits by using equation (3.19)

$$P_{gi}^{j} = P_{gi}^{min} + \frac{P_{gi}^{max} - P_{gi}^{min}}{2^{l}-1} y_i^j \qquad i=1,2,\dots, NG;\ j=1,2,\dots , POP \tag{3.19}$$

$$y_i^j = \sum_{k=1}^{l_i} 2^{k-1} b_{ik}^j \tag{3.20}$$

where

b^j_{ik} is the kth binary digit of the jth string and ith substring

l_i is the length of string of the ith substring

POP is the population size

P_{gi}^{min} is the minimum value of generation of the ith plant

P_{gi}^{max} is the maximum value of generation of the ith plant

y_i^j is the binary coded value of the ith substring

Step 3: Check the constraint violation limit of the decoded binary strings. Only strings that satisfy the constraints are included into population set. This process is repeated iteratively until a fixed size of population is attained.

Step 4: Calculate the power at slack bus according to equation (3.21).

$$P_{NG} = P_D - (P_1 + P_2 + \dots\dots + P_{NG-1}) \tag{3.21}$$

Step 5: Calculate the transmission loss P_{Loss} by using B-loss coefficient formula given in equation (3.4).

Step 6: Losses are incorporated by adjusting the last unit power level as in equation (3.22).

$$P_{NG}^{new} = P_D + P_{Loss} - (P_1 + P_2 + \ldots\ldots + P_{NG-1}) \qquad (3.22)$$

Step 7: Check if $| P_{NG} - P_{NG}^{new} | <= \varepsilon$. Otherwise, update $P_{NG} = P_{NG}^{new}$ and Go to step 5.

Step 8: Calculate the price penalty factor as explained in section [3.4] and objective function value given by equations (3.12-3.15).

Step 9: Fitness value of each binary string is calculated by $F = K \div \varepsilon$

$$\varepsilon = TC + \beta * \left| P_D + P_{Loss} - \sum_{i=1}^{NG} P_{gi} \right| \qquad (3.23)$$

where

NG is number of generator

TC is total operating cost

Step 10: Select the higher fitness values as antigens and lower fitness values as antibodies from the population and calculate the euclidean distance between them using equation (3.24).

$$D = \sqrt{\sum_{i=1}^{l} (abi - agi)^2} \qquad (3.24)$$

Step 11: Clone the population of antibodies and start the maturation process. If D is more select them for hypermutation else simple mutation as shown below.

Before Hypermutation

	↓				↓				↓		
1	1	1	0	0	1	0	1	0	0	1	1

After Hypermutation

1	0	1	0	0	0	0	1	0	1	1	1

Before Mutation

					↓						
1	1	1	0	0	1	0	1	0	0	1	1

After Mutation

1	1	1	0	0	0	0	1	0	0	1	1

Step 12: The mutated clones are decoded and again tested for constraint violation and if satisfied then added into clone population pool and calculate the fitness values for the cloned population.

Step 13: A population of same size is selected from the cloned population based upon their fitness values to retain the same population size.

Step 14: The above process is repeated iteratively until it meets the stopping criteria of maximum number of iterations to get an optimum solution.

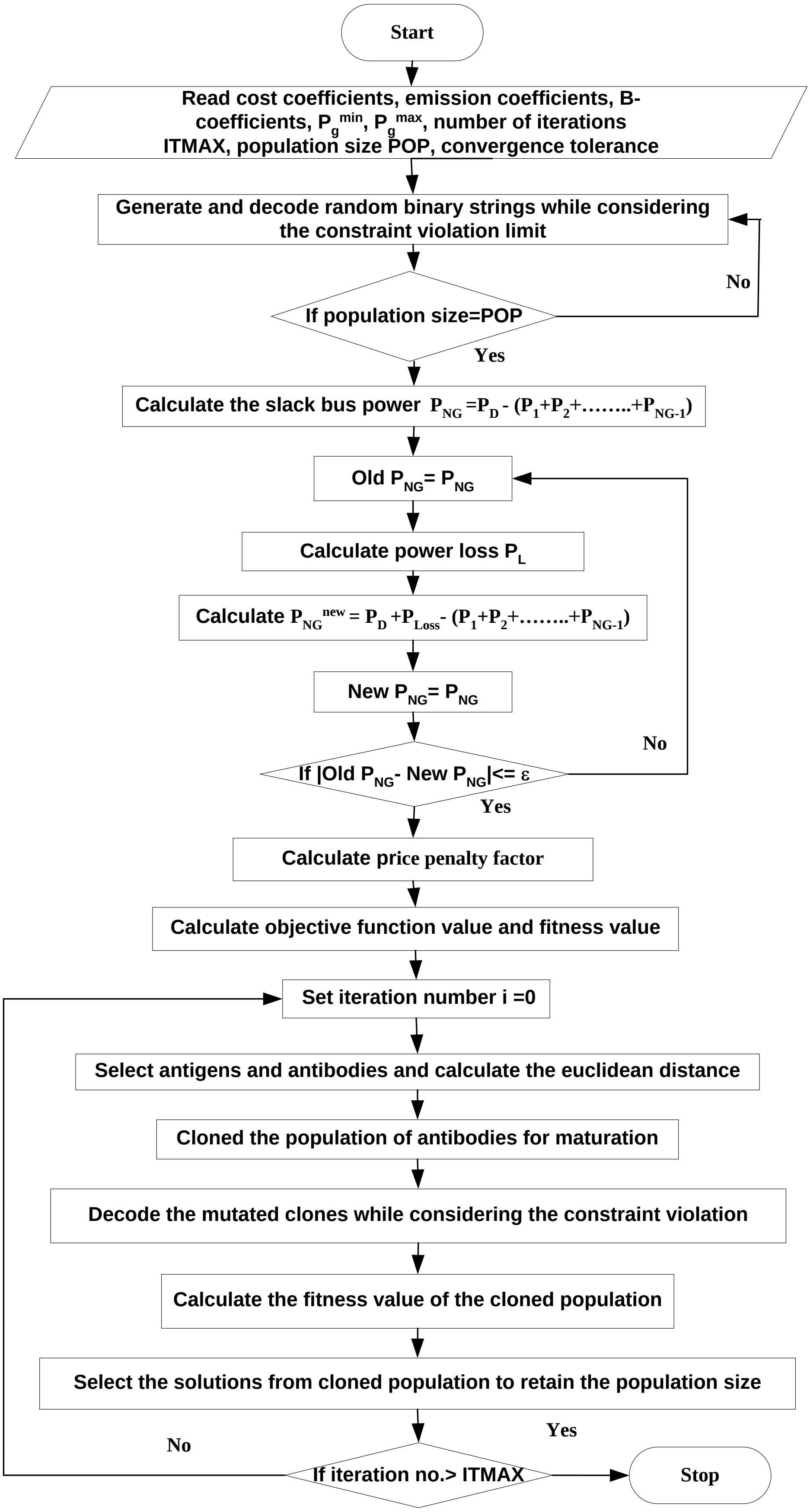


Fig. 3.1. Flowchart of CEED using AIS based price penalty factor approach

3.6 REALIZING CEED USING AIS VIA FUZZY DECISION MAKING

Assumptions made to implement clonal selection algorithm to combine economic and emission dispatch (CEED) problem [32] based on fuzzy decision making are discussed in section [3.5].

Algorithm

The stepwise procedure of AIS for the optimization of generation cost and emission based upon fuzzy decision making approach is listed below. The flowchart to represent algorithm is shown in Fig. 3.2.

Step 1: Read data namely cost coefficients a_i, b_i, c_i, emission coefficients d_i, e_i, f_i, B-coefficients, B_{ij} (i=1,2, ………., NG; j= 1,2, …………, NG), convergence tolerance, maximum and minimum limits of generation of power of each generator, number of iterations ITMAX, String length l and population size POP.

Step 2: Generate a population of random binary strings and decode them to calculate the generating power of each unit between the minimum and maximum power limits of the corresponding unit except at slack bus by using equation (3.19).

Step 3: Check the constraint violation limit of the decoded binary strings. Only strings that satisfy the constraints are included into population set. This process is repeated iteratively until a fixed size of population is attained.

Step 4: Calculate the power at slack bus according to equation (3.21).

Step 5: Calculate the transmission loss P_{Loss} by using B-loss coefficient formula given in equation (3.4).

Step 6: Losses are incorporated by adjusting the last unit power level as in (3.22).

Step 7: Check if $| P_{NG} - P_{NG}^{new} | <= \varepsilon$. Otherwise, update $P_{NG=} P_{NG}^{new}$ and Go to step 5.

Step 8: Calculate fuzzy membership function corresponding to the fuel cost and emission level by using the formula given in equation (3.17) and (3.18) respectively.

Step 9: Calculate the fitness value by selecting a minimum value from both fuel cost fuzzy membership function and emission fuzzy membership function as $\min\{\mu(F_i), \mu(E_i)\}$.

Step 10: Select the higher fitness values as antigens and lower fitness values as antibodies from the population and calculate the euclidean distance between them by using equation (3.24).

Step 11: Clone the population of antibodies and start maturation process as discussed in above algorithm.

Step 12: The mutated clones are decoded and again tested for constraint violation and if satisfied then added into clone population pool and calculate the fitness values for the cloned population.

Step 13: A new population of same size is selected from the cloned population based upon their fitness values to retain the same population size.

Step 14: From new population select the objective function value as $\mu= [\max \{\min (\mu (F_i), \mu (E_i))\}]$.

Step 15: The above process is repeated iteratively until it meets the stopping criteria of maximum number of iterations to get an optimum solution.

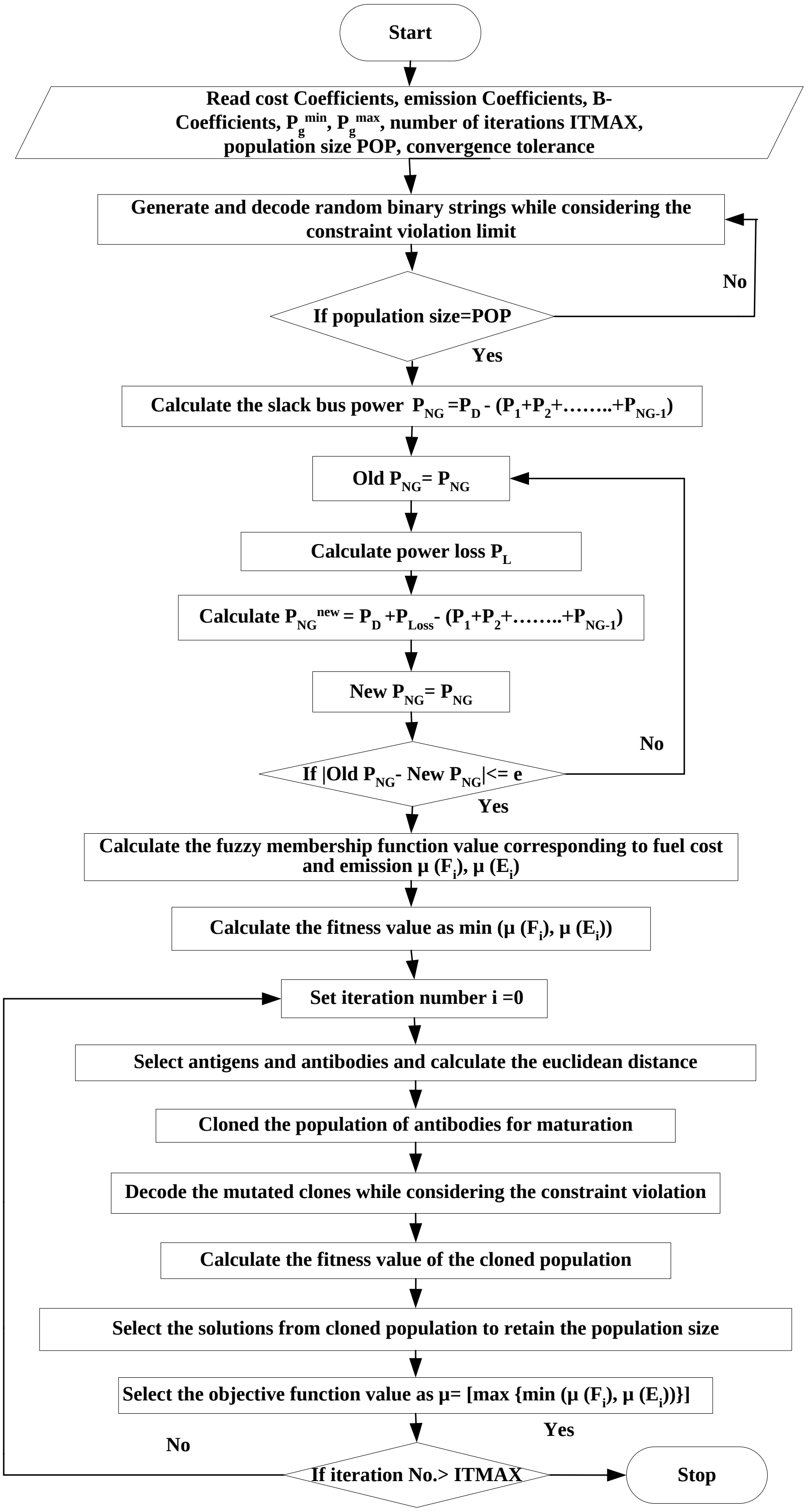


Fig. 3.2. Flowchart of CEED using AIS based fuzzy decision making approach

CHAPTER-4

RESULTS AND DISCUSSION

4.1 INTRODUCTION

In this work, the results have been obtained from the developed algorithm for combined economic and emission dispatch (CEED) based on AIS. The formulation of CEED optimization problem is described in section [3.2]. This problem has been solved by two approaches namely price penalty factor (PPF) and fuzzy decision making (FDM). The formulation of these methods and algorithms are given in section [3.3-3.6]. To describe the effectiveness of proposed algorithm, this algorithm has been tested on two test systems comprising three and six generating units for different load demands. The data for these test systems is given in Appendix I and Appendix II respectively. The results obtained from the proposed method are compared with published results in literature i.e. refined genetic algorithm (RGA) and artificial bee colony (ABC) method.

4.2 RESULTS USING PRICE PENALTY FACTOR APPROACH

The augmented objective function for price penalty factor is given by equation (3.12-3.15). The results are obtained by the algorithm given in section (3.5).

4.2.1 Test case I: Three unit system

In this case study, developed algorithm has been applied for economic dispatch, emission dispatch and combined economic emission dispatch via price penalty factor (CEED-PPF) for three generating units. The results obtained from the discussed method corresponding to the economic dispatch, emission dispatch and combined economic emission dispatch (CEED-PPF) are given in Table 4.1, 4.2 and 4.3 for load demands of 400 MW, 500 MW and 700 MW respectively. The Fig. 4.1 depicts the graph of augmented cost with respect to total number of iterations for a load demand of 400 MW, which is of decreasing nature. The augmented cost is derived from fuel cost and emission by equation (3.12). The graph between fuel cost and emission is plotted as shown in Fig. 4.2 for economic dispatch, emission dispatch and CEED-PPF for 400 MW. These solutions are having the nature of pareto solutions. For CEED, the fuel cost is higher than the cost resulted by economic dispatch while emission is higher than emission value resulted by emission dispatch.

Table 4.1 Results of Economic Dispatch for Case-I

Power Demand (MW)	400	500	700
P_1 (MW)	81.484	105.97	154.67
P_2 (MW)	150.81	193.28	279.8
P_3 (MW)	175.27	212.65	289.27
$\sum P$ (MW)	407.564	511.9	723.74
Power Loss (MW)	7.567	11.902	23.74
Fuel Cost (Rs/hr)	20812	25465	35423
Emission (Kg/hr)	206.6	317.96	660.6

Table 4.2 Results of Emission Dispatch for Case-I

Power Demand (MW)	400	500	700
P_1 (MW)	104.98	131.67	186.06
P_2 (MW)	151.09	189.57	267.5
P_3 (MW)	151.31	190.41	269.72
$\sum P$ (MW)	407.38	511.65	723.28
Power Loss (MW)	7.387	11.653	23.285
Fuel Cost (Rs/hr)	20844	25501	35472
Emission (Kg/hr)	200.14	311.06	651.42

Table 4.3 Results of CEED-PPF for Case-I

Power Demand (MW)	400	500	700
P_1 (MW)	102.68	128.85	182.49
P_2 (MW)	151.06	190.27	269.73
P_3 (MW)	153.66	192.56	271.12
$\sum P$ (MW)	407.4	511.68	723.35
Power Loss (MW)	7.4015	11.676	23.333
Fuel Cost (Rs/hr)	20838	25494	35462
Emission (Kg/hr)	200.21	311.13	651.51
Augmented Cost (Rs/hr)	29809	39435	66619

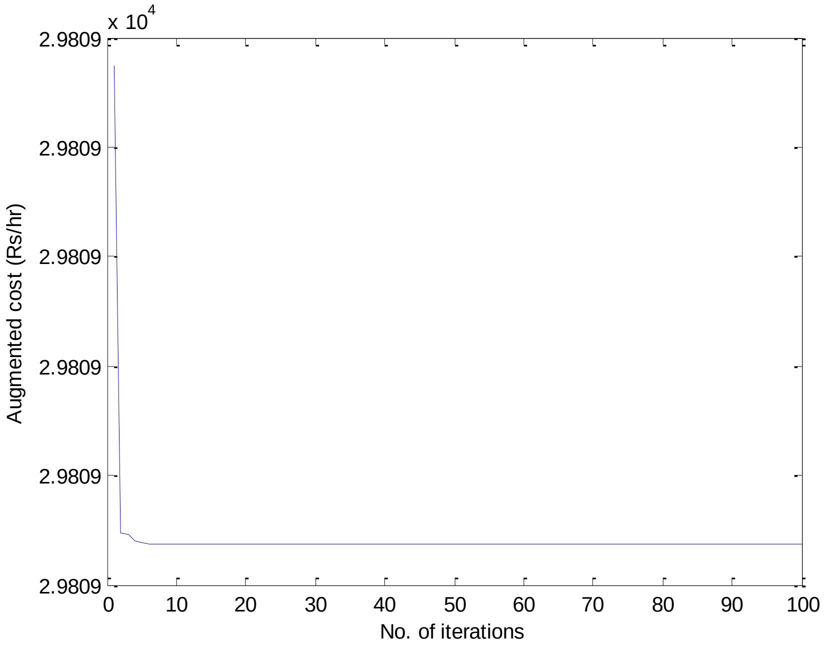


Fig. 4. 1 Change in augmented cost with iterations for CEED-PPF-case I (400 MW)

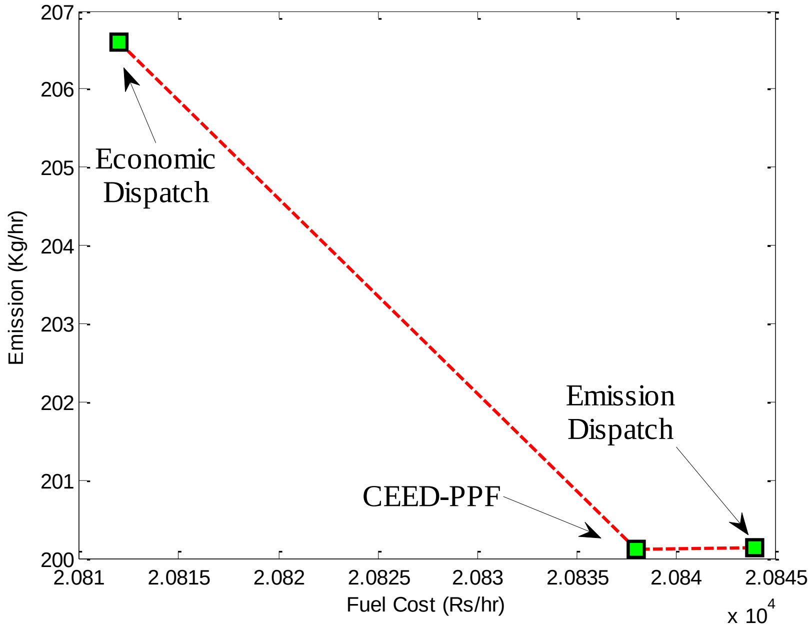


Fig. 4. 2 Representation of economic dispatch, emission dispatch and CEED-PPF – case-I (400 MW)

4.2.2 Test case II: Six unit system

In this case study, developed algorithm has been applied for economic dispatch, emission dispatch and combined economic emission dispatch (CEED-PPF) for six generating units. The results obtained from the discussed method are given in Table 4.4 for load demands of 500 MW and 900 MW corresponding to the economic dispatch, emission dispatch and combined economic emission dispatch (CEED-PPF). The Fig. 4.3 depicts the augmented cost with respect to total number of iterations for a load demand of 900 MW which is of decreasing nature. It is inferred that fuel cost and emission of CEED-PPF lies between the fuel cost and emission obtained from classical economic load dispatch and emission dispatch. The Fig. 4.4 represents the graph between fuel cost and emission for the solutions obtained by economic dispatch, emission dispatch and CEED-PPF for a load demand of 900 MW. These solutions are also the pareto solutions.

Table 4.4 Results of Economic Dispatch, Emission Dispatch and CEED-PPF for Case-II

	Economic Dispatch		Emission Dispatch		CEED	
Power Demand (MW)	500	900	500	900	500	900
P_1 (MW)	18.984	36.953	38.75	119.19	34.398	96.25
P_2 (MW)	20	21.646	42.915	123.59	28.118	97.568
P_3 (MW)	70.625	166.01	89.841	141.88	82.5	149.58
P_4 (MW)	81.17	155.31	78.75	144.38	91.724	147.94
P_5 (MW)	172.32	276.25	130	199.43	137.58	219.48
P_6 (MW)	146.48	275.71	128.38	198.86	134.66	217.21
$\sum$ P (MW)	509.679	931.439	508.636	927.33	508.98	928.028
Fuel cost (Rs/hr)	27488	47047	27796	49570	27617	48414
Emission (Kg/hr)	279.2	818.74	262.14	682.87	263.41	692.6
Power Loss (MW)	9.6783	31.885	8.6338	27.317	8.9832	28.021
Augmented Cost (Rs/hr)	-	-	-	-	38984	81536

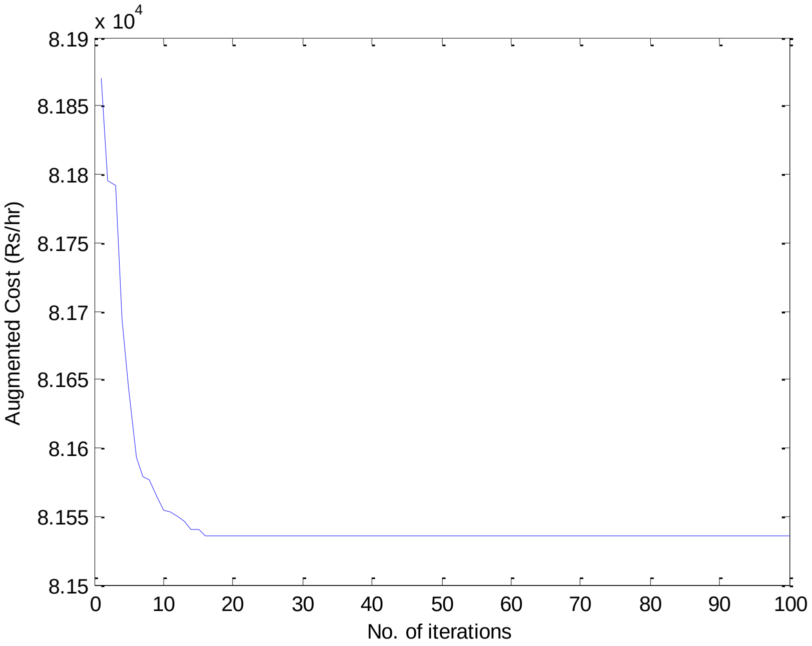


Fig. 4. 3 Change in augmented cost with iterations for CEED-PPF-case II (900 MW)

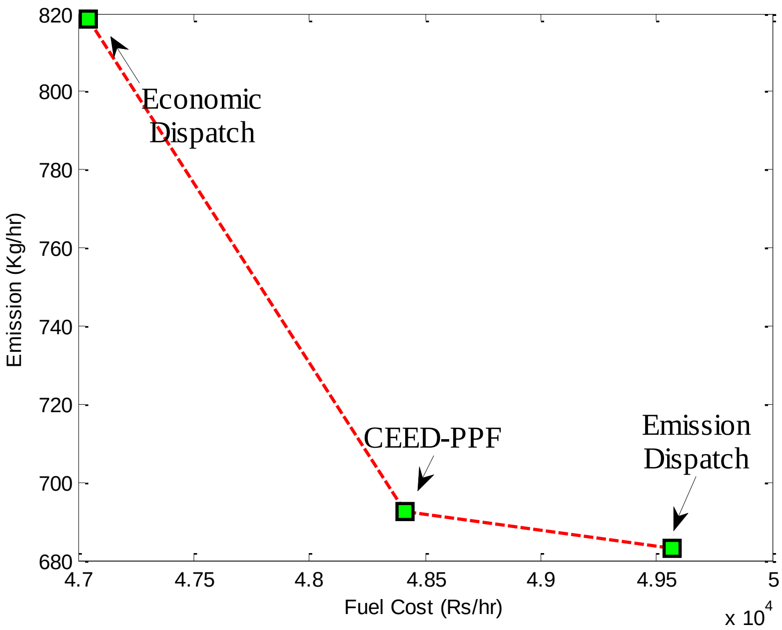


Fig. 4. 4 Representation of economic dispatch, emission dispatch and CEED-PPF – case-II (900 MW)

4.3 RESULTS USING FUZZY DECISION MAKING APPROACH

In case of classical economic load dispatch, the total generation cost comes out to be minimum at the expense of increase in emission whereas in case of classical emission dispatch, the total emission comes out to be minimum at the expense of rise in cost. To find the best solution between economy and emission, the fuzzy decision making (FDM) approach is applied. The membership function for FDM approach is given as equation (3.17-3.18). The proposed approach is applied on three and six generating unit systems to obtain the results for CEED-FDM for different varying load demands.

4.3.1 Test case I: Three unit system

In this case study, developed algorithm with fuzzy decision making approach has been applied for CEED-FDM for three generating units. The results obtained are given in Table 4.5 for a load demand of 400 MW, 500 MW and 700MW. It is inferred that the solution obtained from CEED-FDM lies on the pareto optimal front, plotted with optimal economic dispatch, optimal emission dispatch and CEED-FDM as shown in Fig. 4.5. The Fig. 4.6 represents the convergence of fuzzy membership function for 400 MW. This graph is not having the typical monotonically increase characteristics due to the change in the values of F_{max}, F_{min}, E_{max} and E_{min} in each iteration. However, the optimum solution exhibits the characteristic of pareto solution.

Table 4.5 Results of CEED-FDM for Case-I

Power Demand (MW)	400	500	700
P_1 (MW)	88.32	114.87	170.35
P_2 (MW)	157.29	191.58	273.44
P_3 (MW)	161.91	205.36	279.7
$\sum P$ (MW)	407.52	511.81	723.49
Power Loss (MW)	7.5164	11.803	23.494
Fuel Cost (Rs/hr)	20818	25469	35435
Emission (Kg/hr)	202.75	314.05	653.69

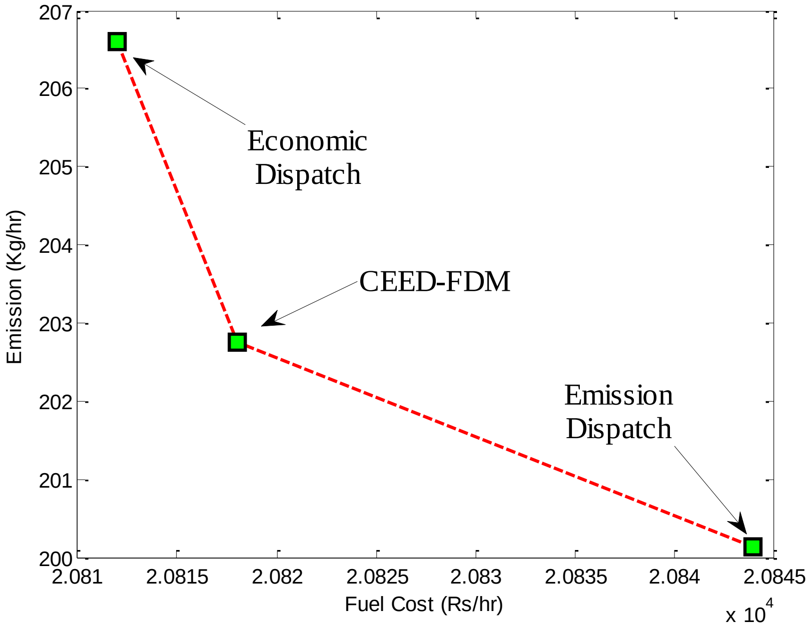


Fig. 4. 5 Representation of economic dispatch, emission dispatch and CEED-FDM case-I (400 MW)

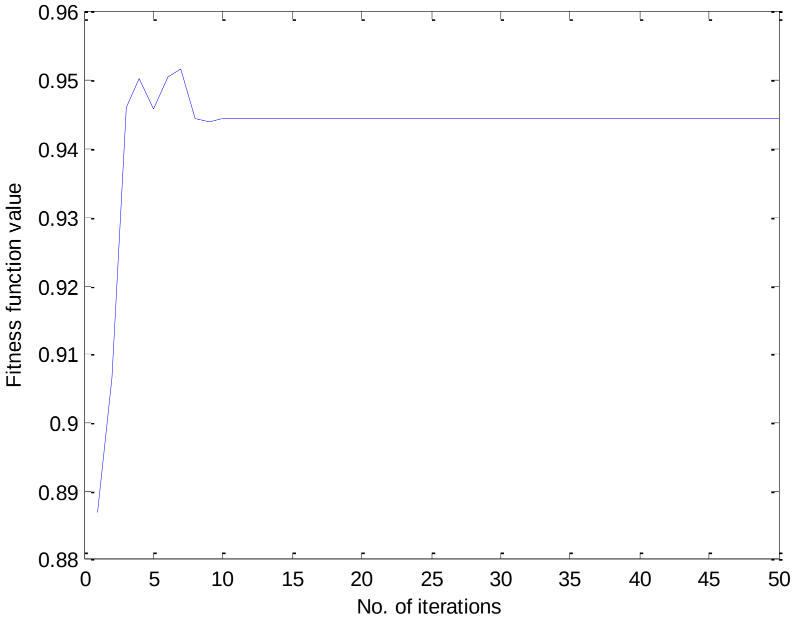


Fig. 4. 6 Representation of fitness function with progress of iterations case-I (400 MW)

4.3.2 Test case II: six unit system

In this case study, developed algorithm with fuzzy decision making approach has been applied for CEED-FDM for six generating units. The results obtained from the discussed approach for CEED-FDM are given in Table 4.6 for load demands of 500 MW and 900 MW. It can be observed from Fig. 4.7 that solution obtained from the CEED-FDM is also the pareto solution. If an optimal pareto front is constructed, it will lie on the pareto optimal front.

Table 4.6 Results of CEED-FDM for Case-II

Power Demand (MW)	500	900
P_1 (MW)	24.375	64.24
P_2 (MW)	20.19	68.401
P_3 (MW)	81.758	162.28
P_4 (MW)	92.764	157.07
P_5 (MW)	149.04	240.24
P_6 (MW)	141.17	236.9
$\sum P$ (MW)	509.297	929.131
Power Loss (MW)	9.302	29.132
Fuel Cost (Rs/hr)	27515	47481
Emission (Kg/hr)	268	729.46

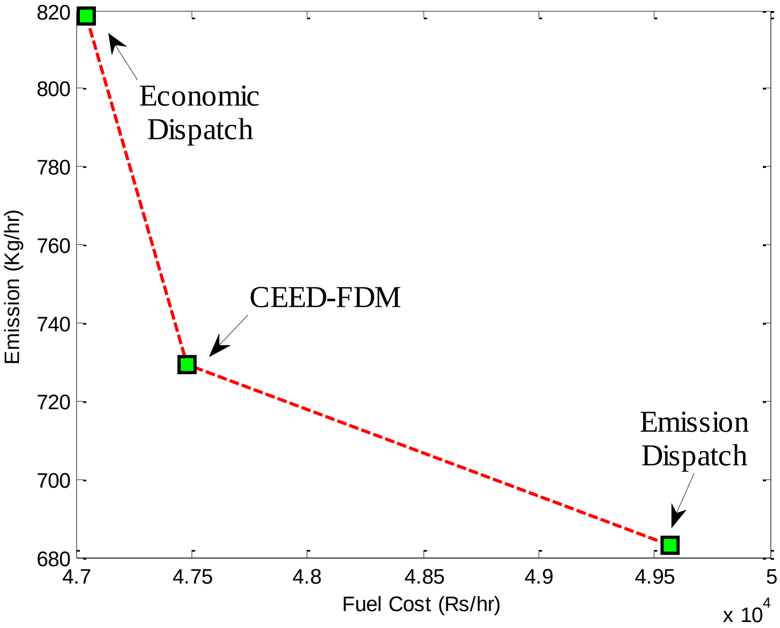


Fig. 4. 7 Representation of economic dispatch, emission dispatch and CEED-FDM case-II (900 MW)

4.4 COMPARISON OF RESULTS

The results obtained from the price penalty factor (PPF) and fuzzy decision making (FDM) approaches based upon artificial immune system (AIS) in section [4.2] and section [4.3]. In this the above results are compared with RGA and ABC methods [45] for three and six generating unit systems.

4.4.1 Test case I: Three unit system

The comparison of results for CEED is given in Table 4.7 for load demands of 400 MW, 500 MW and 700 MW. The range of values of fuel cost and emission are same as reported in literature. Although, the results obtained from price penalty factor method and fuzzy decision method are different, the solutions are non-dominating and both can be regarded as pareto optimal solutions. The pareto front, as shown in Fig. 4.8 for a load demand of 400 MW, the result by CEED-FDM approach is having better diversity as compared to CEED-PPF result.

Table 4.7 Comparison of Result for Various Load Demands Case-I

Power Demand (MW)	Method		Power Loss (MW)	Fuel Cost (Rs/hr)	Emission (kg/hr)	Augmented Cost (Rs/hr)
400	RGA [45]		7.39	20801.8	201.21	29812
	ABC[45]		7.5681	20838	200.2211	29804.5
	AIS	Price penalty factor	7.4015	20838	200.21	29809
		Fuzzy decision making	7.5164	20818	202.75	-
500	RGA [45]		11.70	25491.6	311.33	39433
	ABC[45]		11.6937	25495	311.15	39428.3
	AIS	Price penalty factor	11.676	25494	311.13	39435
		Fuzzy decision making	11.803	25469	314.05	-
700	RGA [45]		23.28	35471.48	651.60	66631
	ABC[45]		23.3664	35464.00	651.60	66622.50
	AIS	Price penalty factor	23.333	35462	651.51	66619
		Fuzzy decision making	23.494	35435	653.69	-

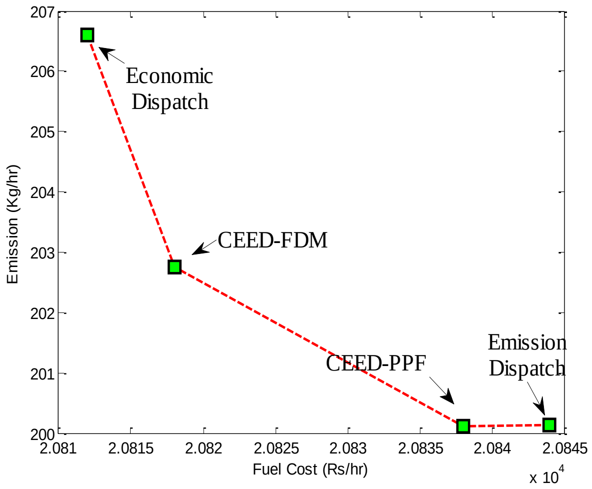


Fig. 4. 8 Comparison of economic dispatch, emission dispatch, CEED-PPF and CEED-FDM-case I (400 MW)

4.4.2 Test case II: Six unit system

The comparison of discussed approaches for CEED is given in Table 4.8 for load demands of 500 MW and 900 MW. The range of the values of fuel cost and emission are same as reported in literature. Here, it is seen that the results obtained from price penalty factor method and fuzzy decision method are different but both of the solutions are non-dominating and can be regarded as pareto optimal solutions. The pareto front for a load demand of 900 MW is shown in Fig. 4.9.

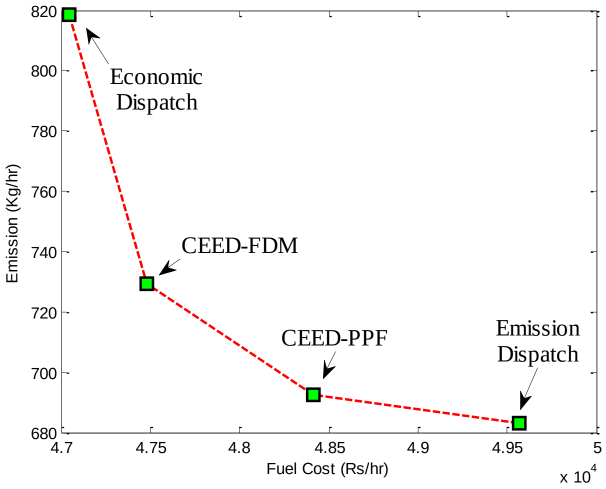


Fig. 4. 9 Comparison of economic dispatch, emission dispatch, CEED-PPF and CEED-FDM-case II (900 MW)

Table 4.8 Comparison of Result for Various Load Demands Case-II

Power Demand (MW)	Method		Power Loss (MW)	Fuel Cost (Rs/hr)	Emission (kg/hr)	Augmented Cost (Rs/hr)
500	RGA [45]		10.172	27692.1	263.472	39258.100
	ABC[45]		8.9343	27613	263.012	39156.9
	AIS	Price penalty factor	8.9832	27617	263.41	38984
		Fuzzy decision making	9.302	27515	268	-
900	RGA [45]		35.230	48892.900	701.428	82436.580
	ABC[45]		28.008	47045.300	693.791	81527.600
	AIS	Price penalty factor	28.021	48414	692.6	81536
		Fuzzy decision making	29.132	47481	729.46	-

CHAPTER-5

CONCLUSIONS AND FUTURE SCOPE OF WORK

5.1 CONCLUSIONS

The clonal selection method based AIS has been applied on combined economic and emission dispatch (CEED) problem. The presented AIS formulation determines the optimum powers generated by each unit to have optimum fuel cost and emission by two alternative approaches namely Price penalty factor (PPF) and fuzzy decision making (FDM). The AIS utilizes adaptive cloning scheme and mutation. The proposed method is applied on three and six generating unit systems and the results are compared with various alternative techniques such as refined genetic algorithm (RGA), artificial bee colony (ABC) to show its effectiveness. The following conclusions are drawn from the study-

- Both the price penalty factor method and fuzzy decision making are giving non-dominating solutions.
- Both the formulations of price penalty factor and fuzzy decision making approaches are simple and the multi-objective problem is represented as single objective optimization.
- The fuzzy decision making is giving good diversity with respect to economic and emission dispatch solutions, and the formation is independent to any penalty or weight factors.

5.2 FUTURE SCOPE OF WORK

The scope of work after studying CEED using AIS is identified as:

- The binary AIS has been used requires large memory and computational effort in decoding. So the AIS with real encoding scheme can be utilized.
- The losses are accounted by B-coefficients and without solving the complete power system. Thereby the power system constraints such as limit on bus voltage, power flow limits are not taken into account. For practical realization these constraints may be accounted and the algorithm can be modified accordingly.

APPENDIX

APPENDIX-I

Input data for 3 generating unit system [45]

Table A.1 Fuel Cost Coefficients for Three Generating Unit System

Unit	Fuel Cost Coefficients			P_g^{min} (MW)	P_g^{max} (MW)
	a_i (Rs/hr)	b_i (Rs/MWh)	c_i (Rs/MW^{2}h)		
G1	1243.53110	38.0553	0.03546	35	210
G2	1356.65929	38.27041	0.01799	125	315
G3	1658.56960	36.32782	0.0211	130	325

Table A.2 Emission Coefficients for Three Generating Unit System

Unit	Emission Coefficients			P_g^{min} (MW)	P_g^{max} (MW)
	d_i (Kg/hr)	e_i (Kg/MWh)	f_i (Kg/MW^{2}h)		
G1	40.26690	-0.5455	0.00683	35	210
G2	42.89553	-0.5116	0.00461	125	315
G3	42.89553	-0.5116	0.00461	130	325

B- Coefficient Matrix for Three Generating Unit System

$$B=\begin{bmatrix} 0.000070 & 0.000025 & 0.000030 \\ 0.000025 & 0.000080 & 0.000032 \\ 0.000030 & 0.000032 & 0.000069 \end{bmatrix}$$

APPENDIX-II

Input data for 6 generating unit system [45]

Table A.3 Fuel Cost Coefficients for Six Generating Unit System

Unit	Fuel Cost Coefficients			P_g^{min} (MW)	P_g^{max} (MW)
	a_i (Rs/hr)	b_i (Rs/MWh)	c_i (Rs/MW^{2}h)		
G1	756.79886	38.53973	0.15247	10	125
G2	451.32513	46.15916	0.105870	20	150
G3	1049.9977	40.39655	0.02803	35	225
G4	1243.5311	38.30552	0.03546	35	210
G5	1658.5596	36.32782	0.02111	130	325
G6	1356.6592	38.27041	0.01799	125	325

Table A.4 Emission Coefficients for Six Generating Unit System

Unit	Emission Coefficients			P_g^{min} (MW)	P_g^{max} (MW)
	d_i (Kg/hr)	e_i (Kg/MWh)	f_i (Kg/MW^{2}h)		
G1	13.85932	0.32767	0.00419	10	125
G2	13.85932	0.32767	0.00419	20	150
G3	40.2669	-0.54551	0.00683	35	225
G4	40.2669	-0.54551	0.00683	35	210
G5	42.89553	-0.51116	0.00461	130	325
G6	42.89553	-0.51116	0.00461	125	325

B-coefficient Matrix for Six Generating Unit System

$$B=\begin{bmatrix} 1.40 & .17 & .15 & .19 & .26 & .22 \\ 0.17 & 0.60 & 0.13 & 0.16 & 0.15 & 0.20 \\ 0.15 & 0.13 & 0.65 & 0.17 & 0.24 & 0.19 \\ 0.19 & 0.16 & 0.17 & 0.71 & 0.30 & 0.25 \\ 0.26 & 0.15 & 0.24 & 0.30 & 0.69 & 0.32 \\ 0.22 & 0.20 & 0.19 & 0.25 & 0.32 & 0.85 \end{bmatrix}$$

LIST OF PUBLICATION

A review paper on “Combined Economic and Emission Dispatch Using Evolutionary Methods” published in International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, IJAREEIE, ISSN (Print): 2320-3765, ISSN (Online): 2278-8875, Vol. 2, Issue 6, June 2013.

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