IMPROVED OPTIMAL ECONOMIC AND ENVIRONMENTAL OPERATIONS OF POWER SYSTEMS USING PARTICLE SWARM OPTIMIZATION

by

Mohammed AlRashidi

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In memory of my beloved father

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List of Abbreviations and Symbols

List of Abbreviations:

EED	Emission-Economic Dispatch
OPF	Optimal Power Flow
PSO	Particle Swarm Optimization
SQP	Sequential Quadratic Programming
GRG	Generalized Reduced Gradient
IEEE	Institute of Electrical and Electronics Engineers
IEE	Institute of Electrical Engineers
FACTS	Flexible Alternating Current Transmission System
NSGA	Non-dominated Sorting Genetic Algorithm
SPEA	Strength Pareto Evolutionary Algorithm
NPGA	Niched Pareto Genetic Algorithm
UPFC	Unified Power Flow Controller
TCSC	Thyristor-Controlled Series Compensation
TCPS	Thyristor-Controlled Phase Shifter
ECD	Economic Cost Dispatch
ED	Emission Dispatch
EA	Evolutionary Algorithms
MOSST	Multi-Objective Stochastic Search Technique
LP	Linear Programming
AHNN	Adaptive Hopfield Neural Network
UF	Utility Function
NR	Newton-Raphson
HPSO	Hybrid Particle Swarm Optimization
SLA	Set to Limit Approach
VAR	Volt-Amperes Reactive
MW	Megawatt

P.U.	Per Unit

List of Symbols:

F	Objective Function
x	The State or Dependent Variables Vector
u	The Control or Independent Variables Vector
g	Set of Equality Constraints
h	Set of Inequality Constraints
S	Feasible Space
G	Number of Objectives
pbest	Particle Best Position
gbest	Global Best Position
c_1, c_2	Two Positive Acceleration Constants
r_1, r_2	Two Randomly Generated Numbers
w	Inertia Weight
a, b, c, e, f	Fuel Cost Function Coefficients
N	Number of Generating Units
P	Real Generated Power
Pmin	Minimum Power Output Limit of a Generating Unit
Pmax	Maximum Power Output Limit of a Generating Unit
P_L	Overall System Real Power Losses
P_D	Total System Real Power Demand
B	Coefficients Loss Matrix
CO_2	Carbon Dioxide
SO_2	Sulfur Dioxide
NO_x	Nitrogen Oxides
E	Emission Function
$\alpha, \beta, \gamma, \zeta, \lambda$	Emission Function Coefficients
η	Weight Factor
D	Price Penalty Factor
V_{max}	Maximum Velocity

h_{min}	Lower Bound on the Inequality Constraint
h_{max}	Upper Bound on the Inequality Constraint
P_{G1}	Slack Bus Real Power Output
V_{LK}	Voltage Magnitude of a Load Bus
θ_{LK}	Voltage Phase Angle of a Load Bus
Q_G	Generator Reactive Power Output
T_K	Transformer Tap Setting
Q_{CK}	Reactive Power Injections Due to Capacitor Banks
g_k	Line Conductance
Y_{ij}	Element of the Y Admittance Matrix
S_L	Apparent Power
Q_d	Reactive Power Demand
R	Line Resistance
X	Line Reactance
B	Line Charging Susceptance

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Abstract

Power utilities have been facing new challenges in the past few decades that require changes to their traditional operational practices. Two of the main challenges are the rising concerns about the harmful impacts of electric power production on the environment and the deregulation of the electric power industry. In the past few decades, environmental awareness led to the adoption of rigid environmental policies on power utilities to regulate their emissions. One way to cope with this problem is to dispatch power with environmental considerations. The emission-economic dispatch is an extension of the traditional economic cost dispatch where the ultimate goal is not only to minimize the total production cost but rather to minimize both the production cost and emission of the generating units. Deregulating the power industry also created a highly vibrant and competitive market in which major market players strive to maximize their profits while meeting their other system-wide obligations. One way to do this is to develop a more precise system modeling that eliminates oversimplified assumptions included in representing the original system.

This thesis addresses two main problems commonly encountered in studies related to power system analysis, namely the emission-economic dispatch and optimal power flow. The former is formulated as a nonlinear multi-objective optimization problem with conflicting objectives and subjected to both equality and inequality constraints. The latter problem is formulated as a mixed integer optimization problem with various objectives, i.e. emission, fuel cost, and real power losses, in which some are of non-convex and non-differentiable nature. In both studies, special attention is paid to the environmental and economical aspects of electric power generation.

Numerical solutions to the two problems are investigated via particle swarm optimization (PSO) based algorithms. PSO is a new metaheuristic optimization method which is receiving additional attention recently for several reasons. Modifications and enhancements of the PSO are presented to improve its performance and to make it more suitable to some specific power system problems. Special treatments of control variables and improved constraints handling mechanisms are proposed to tailor the PSO to the aforementioned problems. In the emission-economic dispatch problem, a PSO approach is developed to capture the shape of the Pareto optimal solution set that shows the trade-off relationship between competing objectives. Two aggregation methods are used and analyzed to combine the conflicting objectives. The nature of the control variables and the objectives considered in the optimal power flow study are troublesome to most derivative-based optimization algorithms. Therefore, a hybrid PSO algorithm is developed to overcome such difficulty with promising results. The proposed algorithms are tested on various testing systems and their performances are compared to other optimization techniques. Results indicate the promising potential pertaining to PSO applicability to some of the commonly formulated optimization problems in power systems.

Chapter 1
Introduction

1.1 Motivation

Several factors have played a major role in drastically changing the nature of electrical power industry worldwide. Electric power deregulation that has been taking place in many parts of the world in the last two decades has led to the introduction of new philosophies of operating the electric power system. Policies, interactions, and objectives of different entities of the power industry have been fundamentally revised to cope with the new competitive environment. This has created a highly vibrant and competitive market in which all major players, in this case generation, transmission, and distribution companies, strive to maximize their profits while meeting their other system-wide obligations. One way to accomplish this goal is to develop a more precise system modeling that eliminates oversimplified assumptions included in earlier system representation. Even though the electric power system infrastructure has not changed much since it has been restructured, the rules governing the game have changed considerably.

A simple example illustrating one of the changes that has been introduced as a result of deregulation is the case of operating pumped storage units. Prior to power system restructuring, pump storage units made use of the excess power generated during low demand periods to pump power to the upper reservoir as a means of storing electrical power. This stored energy is then released to shave peak load periods, i.e. its operation closely followed the load profile. Nowadays, the operation of pump storage units relies heavily on following the market clearing price patterns in the electricity market. This means that to optimize the overall profit, the units should store energy (pumping mode) during low market clearing price periods and release it (generating mode) when the price of electricity is high. This new operation concept totally alters the old direct correlation between the load profile and the operation status of the pump storage units.

The impact of power plants on the environment is another issue that has changed some aspects of operational practices. Up until the last few decades, power plants produced electricity without much concern regarding how their emissions impacted the surrounding living species. However, recent awareness of the harmful effects of pollutants emitted as a result of fossil-based power generation and strict environmental laws imposed on electricity producers led to the incorporation of environmental considerations governing the methods by which the electrical power is being produced. This factor prompted revisions to the concept that the optimal operations criterion is measured only by minimizing the overall electricity production cost. Both emissions and fuel costs have to be considered simultaneously to provide a real measure of optimal operations.

Power system networks are considered the most complex man-made inventions of the past two centuries for various reasons. Among these reasons are their wide geographical coverage, various transactions among different utilities, and diversity among individual electric power companies' layouts, size, and equipment used. There are different areas of electric power system analysis which one has to fully understand in order to optimally study, monitor, and control different aspects of such sophisticated systems. Some of the main areas are economic dispatch, unit commitment, state estimation, automatic generation control, and optimal power flow.

An optimal operation strategy in each of the above mentioned areas is required to improve the overall system's economy and efficiency. There are several problems associated with each area that are usually modeled mathematically as solving some type of optimization problems. There are two main categories of optimization problems: linear and nonlinear, these are typically based on the shape of the objective function and/or its constraints. There are various optimization techniques which were developed to suit a certain category. Most of the traditional optimization methods depend on gradient or higher order derivative information to guide the search for an optimal solution. This dependency imposes restrictions on developing precise models for a given system. Another shortcoming of traditional optimization methods is the underlying assumptions of the objective function's shape, i.e. in terms of convexity or concavity requirements. Such assumptions make the optimization approach local in nature (i.e. converge to a local solution instead of the global one) while many problems in power systems have multimodal characteristics.

The drawbacks of traditional optimization algorithms and restrictions imposed on system modeling shifted the attention to the development and adoption of new modern techniques to improve operational strategies. Recently, metaheuristic techniques have been getting added attention as competitive methods to supplement traditional optimization algorithms for a variety of reasons that will be discussed in later chapters. There are some cases in which traditional algorithms are incapable of handling certain optimization problems because of their complex mathematical modeling requirements. Most metaheuristic techniques are inspired by natural phenomena, with many appealing features such as a reliance on simple conceptual ideas that govern their performances, ease of algorithms implementation in general, degree of flexibility to handle different classes of optimization problems, and the ability to be integrated with other search methods.

1.2 Thesis Objectives

Optimal operation of power systems while accounting for environmental aspects is the main focus of this thesis. The goal is to address two main problems; namely emission-economic dispatch (EED) and optimal power flow (OPF) problems. The former is formulated as a multi-objective optimization problem with two types of competing objectives while the latter is formulated with different types of objectives. In the EED problem, the aim is to attempt to solve the problem when environmental issues are considered. The relationship and interaction between the two different types of objectives is to be addressed and analyzed. In solving the OPF problem, an investigation of more precise modeling of the system is presented that is usually oversimplified due to its challenging mathematical properties. Such properties cause difficulties within the context of problem optimization especially with classical optimization methods.

Such complexity in the nature of power systems made its analysis, planning, and monitoring a rather tedious task. This emphasizes the need to develop modern tools to design, analyze, and monitor electric power systems. In this thesis, the goal is to study, understand, and develop the Particle Swarm Optimization technique (PSO) as a new metaheuristic method with global searching capabilities to solve power system optimization problems. Therefore, an attempt is made to modify the algorithm to explore its potential to suit some of the optimization problems that exist in the area of power systems analysis. Finally, its performance in solving different problems is investigated and compared to other commonly used optimization techniques and methods.

1.3 Thesis Contributions

The process of producing this thesis led to a number of contributions in the area of power system economics and operations and the development of particle swarm optimization theory. The following are the major contributions:

1. Providing comprehensive coverage of PSO applications and developments in the area of electric power system operations. State of the art reviews of the problems addressed in this thesis, i.e. EED and OPF, are presented and categorized based on the solution method.
2. Developing an enhanced novel PSO algorithm to solve the EED problem. The novelty of the proposed algorithm arises from the fact that it solves these problems using the fuel cost and emission as direct objective functions instead of using augmented functions to incorporate problem constraints as additional terms. This

overcomes some of the difficulties associated with augmented objectives that will be discussed in more details in a later chapter.

3. Proposing a novel equality constraint handling mechanism which is developed to enforce the optimizer to satisfy the equality constraints of the EED problem throughout the optimization process.
4. Developing an inequality constraint handling strategy that efficiently makes use of memory elements of PSO to improve its overall performance.
5. Implementing an algorithm that captures the Pareto optimal set showing the compromise solutions between two conflicting objective functions, i.e. the fuel cost and emission functions. This proposed algorithm can be adopted to solve other multi-objective optimization problems found in other areas in electric power systems.
6. Developing a hybrid algorithm that combines a discrete version of PSO with the Newton-Raphson technique of solving nonlinear equations to solve a mixed integer nonlinear OPF problem with different objectives being considered. The objectives considered in this study are the fuel cost (convex and non-convex), emission, and real power losses. The proposed algorithm handles different types of control variables, i.e. continuous and discrete variables.

1.4 Thesis Outline

The main tasks that led to the development of this thesis are detailed in seven chapters. Chapter 1 highlights the motivation behind this research project. It also lists the main objectives of the thesis along with its main contributions. Chapter 2 addresses briefly some fundamental concepts of optimization theory that are directly related to the scope of this research. In addition, it provides a general discussion of solution methods commonly used to solve optimization problems. Chapter 3 presents the main elements of PSO theory and its differences from other optimization techniques. Some real world applications based on PSO theory are also listed in this chapter. In chapter 4, a recent and detailed state of the art review is presented. The three main areas covered in this review are: PSO applications in power systems, EED, and OPF. Chapter 5 deals with the EED problem formulation and the proposed solution method along with simulation and results. Chapter 6 addresses the OPF formulation along with the proposed solution approach. Testing results of the proposed approach to the OPF problem are also included in this chapter. Chapter 7 provides concluding remarks and possible future extensions to the research of this thesis.

Chapter 2

Optimization Theory

2.1 Introduction

Optimization can be simply described as the process of finding the best solution that optimizes (usually minimizes or maximizes, but also can be equal to) a certain objective function while satisfying a number of restrictions. Constructing a valid optimization model involves identifying the following three elements [1]:

1. An objective function that gives a measure to the quality of the solution obtained. It can be a linear or nonlinear function.
2. Decision (sometimes called optimization or control) variables in which a proper combination will yield an optimal solution that optimizes the objective. They are categorized as binary, discrete, continuous variables, or combinations of the aforementioned types.
3. Model constraints or restrictions that impose limitations on the decision variables. Typically, model restrictions are represented by either equality or inequality constraints.

Throughout this thesis, discussion will focus on objective function minimization instead of maximization. However, the thesis findings are also applicable to maximization problems since they can be easily converted to minimization ones. Optimization problems are modeled mathematically as follows:

$$Min \;\; F(x,u) \tag{2.1}$$

subject to

$$g(x,u)=0 \tag{2.2}$$

$$h(x,u)\leq 0 \tag{2.3}$$

where

F is the objective function to be minimized.

x is the state or dependent variables vector.

u is the control or independent variables vector.

g is a set of equality constraints.

h is a set of inequality constraints.

Optimization problems are widely encountered in various fields of science and technology. Sometimes such problems can be very complex due to the actual and practical nature of the objective function or the model constraints. Traditionally, derivative-based optimization methods such as sequential quadratic programming methods, Newton's method, reduced gradient method, Hessian-based method, conjugate gradient method, dynamic programming, branch and bound, integer programming, and generalized reduced gradient method are commonly used to solve nonlinear optimization problems [2-4]. These techniques are robust and have proven their effectiveness in handling many classes of optimization problems. However, such techniques can encounter difficulties such as becoming trapped in local minima, increasing computational complexity, and not being applicable to certain classes of objective functions. This led to the need for development of a new class of solution methods that can overcome these shortcomings. Metaheuristic optimization techniques are fast growing tools that can overcome most of the limitations found in derivative-based techniques.

Metaheuristic or modern heuristic optimization techniques have emerged in recent years as viable optimization tools that can replace and sometimes outperform conventional optimization methods. The term "metaheuristic" originates from two Greek words: meta and heuristic. Meta is a Greek prefix that stands for "beyond in a higher level" while heuristic means "to find" [5]. The most popular heuristics algorithms, in chronological order, are evolutionary programming (1960), genetic algorithm (1975), Tabu search (1977), simulated annealing (1985), ant colony optimization (1991), and PSO (1995).

2.2 Global Versus Local Optimization

Mathematical properties of the optimization model infer some information about the characteristics of the optimization problem and solution method. It is very important to identify some of the objective function and/or constraint characteristics before selecting the most suitable solution method. Convexity is among the issues that one must carefully analyze since it determines whether the obtained solution is a global minimizer or a local one. A solution, x^*, is a global minimum of the function f if

$$f(x^*) \leq f(x) \text{ for all } x \in S \tag{2.4}$$

where S is the entire feasible region. If the objective function to be minimized is a convex function, then the local solution is also a global one. For a graphical illustration, consider a single variable function shown in Figure 2.1.

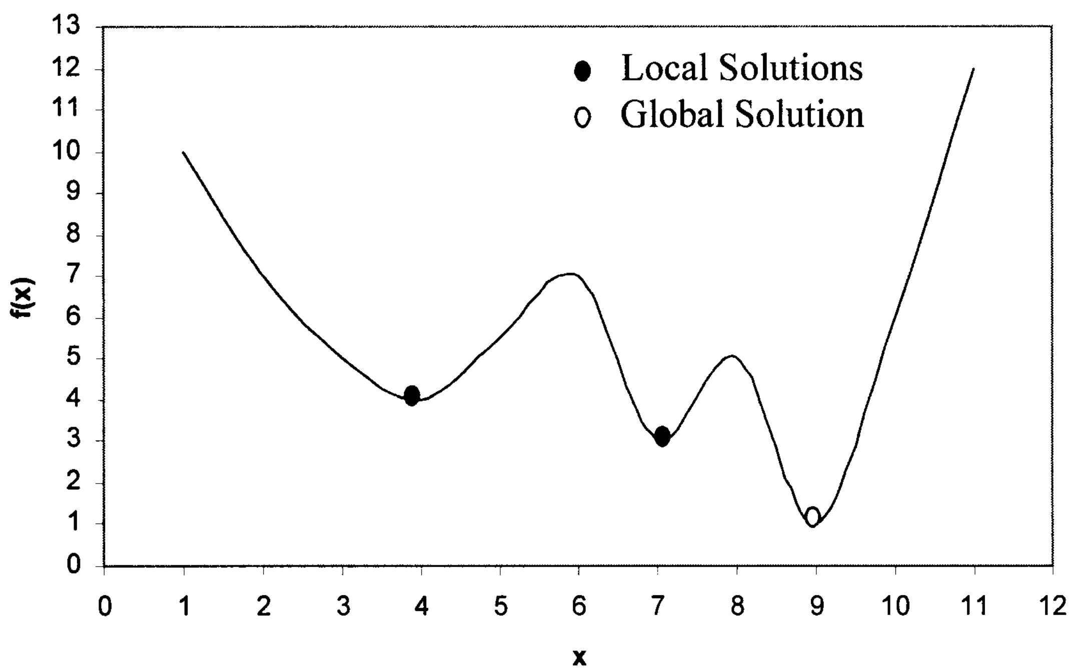

Figure 2.1. Difference between local and global solutions.

There are three extreme points, of which one is global and the remaining two are considered locals. The two local solutions are $x_1 = 4$ and $x_2 = 7$ while the global one is at

x_3 = 9. To further elaborate about one of the major drawbacks of gradient-based optimization algorithms when handling non-convex objectives, suppose the solution space in Figure 2.1 is divided into three convex subsets namely S_1, S_2, and S_3. These subsets of the solution feasible region are defined as follows:

$$S = \begin{cases} x \in S_1 \text{ iff } x \in [1,6] \\ x \in S_2 \text{ iff } x \in]6,8] \\ x \in S_3 \text{ iff } x \in]8,11] \end{cases} \tag{2.5}$$

Since gradient-based optimization algorithms rely on Kuhn-Tucker conditions (i.e. when the derivative vanishes) as termination criteria to detect stationary points, if the initial guess selected to start the optimization process happens to be in subsets S_1 or S_2 the algorithm will converge to x_1 or x_2 respectively. In this case, conventional optimization methods that depend on gradient information might fail to detect global solutions. Additional difficulties rise when constraints are presented in the problem as depicted in Figure 2.2. In this case, the optimal solution is not found at the bottom of a valley, i.e. when the derivative equals zero, but instead it is located at the edge of the feasible search space.

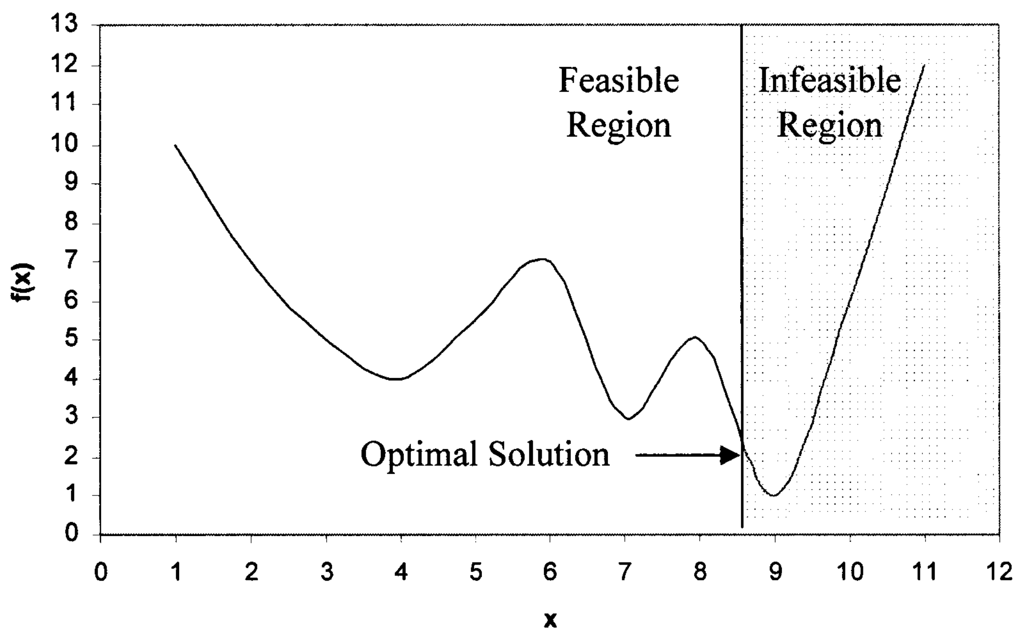

Figure 2.2. Effect of constraints on locating optimal solution.

2.3 Categories of Optimization Problems

Optimization problems can be categorized in many different ways. It seems that there is no standard way of classifying optimization problems. In an attempt to inform the readers of the work yet to come in this thesis, the following classifications are made to cover the wide classes of optimization problems:

1. Nature of the model: This determines whether the optimization model used to formulate the problem is linear or nonlinear. Also, it shows if it is a constrained or an unconstrained model. Sometimes, even the nonlinear category is divided into sub-categories like quadratic, convex, and geometric.
2. Type of solution sought: This determines whether the targeted solution is global or local.
3. Nature of the optimization variables: In this case, optimization variables can be categorized into continuous, discrete, or a combination of the two.
4. Solution update mechanism: Most optimization problems are solved by means of iterative techniques. Some of the solution methods, like in the case of gradient-based methods, use deterministic transition rules to update the solution between two consecutive iterations. On the other hand, some of the derivative-free techniques make probabilistic transitions to modify the search direction between two consecutive iterations.

2.4 Multi-Objective Optimization

Multi-objective optimization problems (also known as vector optimization or multi-criteria) are widely encountered in many real world applications such as those treated in this thesis. Unlike the case of single objective optimization in which one function is being optimized, multi-objective optimizations minimize a number of objectives simultaneously. Mathematically, it can be expressed as follows:

$$Min\ \ F(x,u)=\begin{bmatrix} f_1(x,u) \\ f_2(x,u) \\ \vdots \\ f_G(x,u) \end{bmatrix}\ \text{, where } G = \text{number of objectives} \tag{2.6}$$

In most cases these objectives are incommensurable and conflicting in nature, i.e. there is no single solution that optimizes all objectives concurrently. Therefore, instead of targeting a single solution, an entire set of compromising and non-dominated (also called non-inferior) solutions known as a Pareto optimal set is computed. A feasible vector solution X_1 is said to be a non-dominated solution if there exists no other feasible solution X_2 such that $f_i(X_2) \leq f_i(X_1)$ with respect to all of the objectives. In other words, a solution X_1 is called Pareto optimal if there is no other feasible solution X_2 that would further minimize any objective function without causing a simultaneous increase in at least one objective. The entire set of Pareto optimal solutions (called Pareto front) shows the trade offs among different competing objectives. It is common in multi-objective optimizations to capture such a front as shown in Figure 2.3 for a bi-objective case [6].

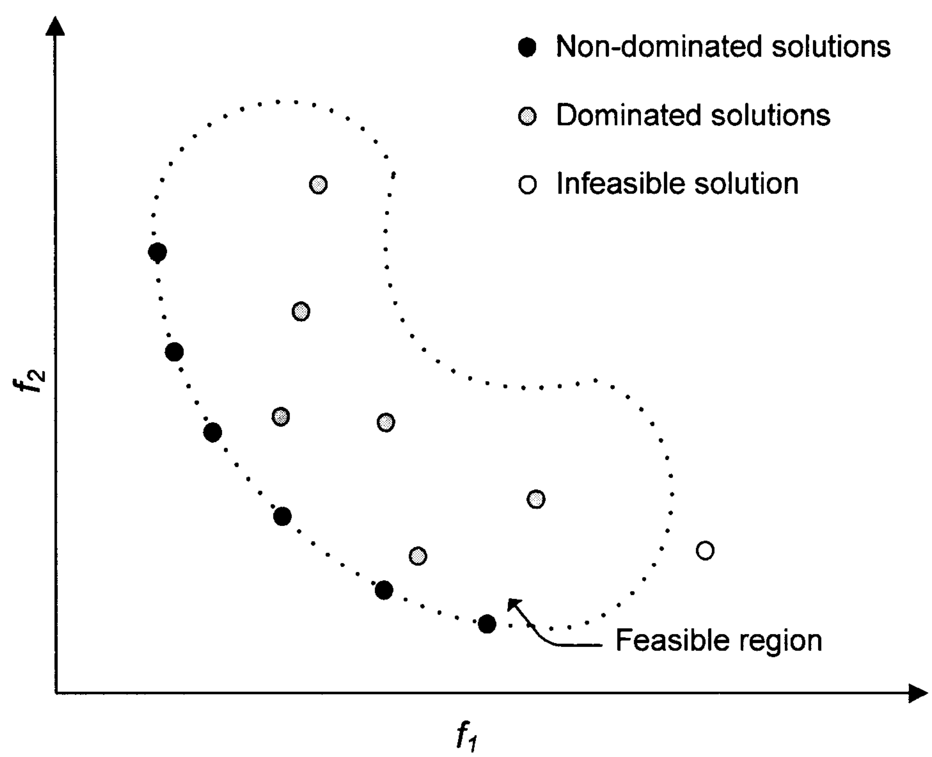

Figure 2.3. Dominance concept for a bi-objective case.

2.4.1 Aggregation Methods

Various methods were developed to deal with multi-objective optimization problems by generating Pareto optimal sets. Aggregation techniques are by far the most common approaches to handle optimization problems in which several objectives are considered. The idea of these aggregation approaches is to convert the multi-objective problem into a single scalar problem and then the problem is solved via any suitable optimization method. Many aggregation techniques have been proposed to handle the problem such as:

1. Goal programming [7]: Goal programming is implemented by assigning a goal or value to be achieved for each objective function. These values are then incorporated into the problem as additional constraints. Subsequently, the problem is solved by minimizing the absolute deviations of the targeted values to the objectives. This algorithm requires prior knowledge about the solution feasible space. Goal programming becomes inefficient if any of the goals selected becomes infeasible.
2. Weighting method [8]: This method simply assigns different weights to each objective function based on its importance and combines different objectives into one single objective function. The result of solving the problem using this approach is highly dependant on the assigned weights. A major drawback of this technique is that very little is known about how to select the proper weights. However, the Pareto front can be obtained by minimizing the aggregated objectives using different weights. This method is very efficient computationally in generating non-dominated solutions.
3. ε-constraint method [9]: In the ε-constraint method, one of the objective functions is selected as the primary objective and the remaining functions are treated as constraints bounded by some proper value of ε. This ε is the maximum allowable value of a given non-primary objective function. Time consumption is one major

disadvantage of this approach since ε has to be updated quite frequently for each objective function [10].

2.5 Solution Methods

This thesis focuses on some of the optimization problems typically encountered in the area of power systems that are nonlinear in nature. Thus, a brief description of most well known solution methods developed to solve such problems is presented. They are mainly classified into two main categories:

2.5.1 Traditional Nonlinear Optimization Techniques

Most traditional nonlinear optimization methods are based on calculus theory in which some operators, such as gradient and/or Hessian are used to guide the search process in locating the optimal solution. This type of solution method is considered the most dominant, and it is widely used in many industrial applications. There are abundant optimization programs that integrate these techniques in order to solve difficult constrained optimization problems. The following is a list of the most robust and well established traditional optimization techniques [1]:

1. Sequential linear programming: This method finds the solution to the nonlinear optimization problem by solving a series of linear programming problems. It successfully linearizes the original problem around the search point using first-order Taylor series expansion. Then, the resulting linear programming problem is solved by the simplex method or any of its variants.
2. Sequential quadratic programming (SQP): As the name indicates, the solution to the original nonlinear problem is obtained by solving an approximate quadratic programming problem in each major iteration. This method involves three major steps: updating the Hessian of the Lagrangian function, solving the quadratic programming sub-problem, and performing a line search.

3. Generalized reduced gradient (GRG): This is an extended version of the reduced gradient method that was developed originally to solve nonlinear optimization problems with linear constraints only. The idea behind this method is to reduce the number of independent optimization variables in the original objective function by manipulating the equality constraints.
4. Sequential unconstrained minimization technique: In this approach, the constrained optimization problem is transformed to an unconstrained problem by introducing additional terms in the original objective to account for the constraints. Penalty function and Lagrangian multiplier methods belong to this category of solution methods, in which additional terms are used in the objective to force feasibility of the obtained solution.

It appears that the generalized reduced gradient and sequential quadratic programming and their variants are the most robust and efficient nonlinear optimizers for large scale optimization problems [11].

2.5.2 Modern Optimization Techniques

A new category of non conventional or metaheuristic optimization tools has emerged to cope with some of the traditional optimization algorithms' shortcomings. The main modern optimization techniques include evolutionary programming, genetic algorithms, evolutionary strategies, artificial neural networks, simulated annealing, ant colony optimization, and PSO. Most of these relatively new developed tools mimic a certain natural phenomenon in their search for an optimal solution like species evolution (evolutionary programming, genetic algorithm, and evolutionary strategies), human neural systems (artificial neural network), thermal dynamics of a metal cooling process (simulated annealing), or social behavior (ant colony optimization and PSO). They have been successfully applied to wide range of optimization problems in which global solutions are more preferred than local ones or when the problem has non-differentiable regions. Also, they are known for their capability to quickly search a large solution space. The following is a brief description of these optimization techniques:

1. Evolutionary programming: evolutionary programming and evolutionary strategies are probably the oldest evolutionary algorithms used to solve optimization problems. Evolutionary programming, along with genetic algorithm and evolutionary strategies, adapt the concept of natural evolution or survival of the fittest founded in the Darwinian Theory of Evolution to enhance the population or "solutions" quality. It was first introduced by Fogel in 1964 as findings of his doctorate work [12]. The evolutionary programming paradigm emphasizes the relationship between ancestors (parents) and their descendants (offspring) and it relies exclusively on a mutation operator to produce offspring, i.e. there is no recombination operator.
2. Evolutionary strategies: The German researchers Rechenberg *et al.* developed evolutionary strategies in 1965 to successfully solve difficult engineering optimization problems when they encountered difficulties in applying gradient based methods [13]. Evolutionary strategies make use of both mutation and recombination operators to produce a new population. Typically, different sizes of parent and offspring populations are used in evolutionary strategies implementation.
3. Genetic algorithm: Genetic algorithm (originally termed reproductive plans) is by far the most commonly used and well developed evolutionary technique with an abundant number of applications and developments found in technical articles and books. It was introduced by Holland in 1975 in an attempt to develop a technique that enables computer programs to mimic the evolution process [14]. In addition to the selection, crossover, and mutation operators, some genetic algorithm-based approaches implement memory elements to preserve the elite solutions [15]. In most genetic algorithm approaches, the binary representation is used for parameter encoding to unify the recombination and mutation operators. However, more recent advances in genetic algorithm approaches elevated its capabilities to

represent solutions using floating point arithmetic. Genetic programming is an extension of genetic algorithm in which individuals are represented as trees.

4. Artificial neural network: Hopfield and Tank introduced a special type of neural network to solve the famous traveling salesman combinatorial problem in 1985 [16]. In this neural network architecture, some of the outputs are fed back to the neurons in the input layer. Parallel data processing and fast network convergence are key features of this approach.
5. Simulated annealing: This optimization technique was proposed independently by Kirkpatrick *et al.* in 1983 [17] and by Cerny in 1985 [18]. Simulated annealing emulates the physical gradual cooling process (called annealing) to produce high quality crystals, i.e. better strength properties, in metals. In both papers, simulated annealing was introduced to solve combinatorial problems by adapting the crystallization process model developed by Metropolis *et al.* [19].
6. Ant colony optimization: Dorigo invented ant colony optimization as a new metaheuristic optimization tool in the early 1990s as he was inspired by the foraging behavior of some ant species. Solution candidates, called ants in ant colony optimization, communicate with other members of the ant colony by depositing pheromones to mark a path. High concentrations of pheromones indicate more favorable paths that other members should follow in order to reach the optimal solution. The original version of ant colony optimization published in references [20;21] was called the ant system and it inspired many researchers to modify and adapt the original ant colony optimization to suit various optimization problems.
7. PSO: This is the main tool used in this thesis and an entire chapter will be dedicated to provide more in depth discussion of this subject.

Other non-classical optimization tools are Tabu search, pattern search, differential evolution, and cultural algorithms. However, these techniques are currently not as popular and the discussion of this thesis is limited to the most commonly used techniques.

2.5.3 Traditional Versus Non-Classical Optimization Methods

Derivative-based optimization algorithms are by far the most common tools being used in most existing applications. This is due to their effectiveness in solving convex optimization problems, solid mathematical foundation, and vast software availability that incorporate these algorithms. However, new developments in non-classical methods are shifting the focus to confidently adapt metaheuristic tools to similar or more complex problems. There are some major differences between metaheuristic and classical optimization methods that can be summarized as follows:

- Most metaheuristic methods are population-based methods that search the solution hyper space by a group of possible solutions. In contrast, classical methods use a single path to search for the optima. This difference enhances the chances of locating the near global solution in metaheuristic methods. It also makes it more suitable to search solution hyper space with non-smooth characteristics. Moreover, it reduces the dependency of successful convergence on the starting search point since most classical methods require a "good" starting point to ensure successful convergence.
- Metaheuristic methods include randomness into their transition rules to move from the current solution to the next one, while classical methods apply deterministic transition rules. This stochastic nature of the transition rules makes the metaheuristic methods less likely to get trapped in local optimum points.
- Metaheuristic approaches are general purpose tools that can suit various optimization problems i.e. linear, nonlinear, discrete, continuous, mixed type, constrained, and unconstrained, with minor modifications. This is due to the fact that they are derivative-free tools that require only a fitness function to measure the "goodness" of a given solution with simple yet effective ways to handle constraints. In general, they require more fitness evaluations with less computation efforts than those of the classical methods.
- Metaheuristic methods with their population-based features can be adapted to serve as niching algorithms in which multiple solutions are tracked upon convergence instead of a single one. In optimization problems with multimodal characteristics, it is

sometimes important to identify all solutions rather than the global one. This is one way to expand the capabilities of metaheuristic tools to perform parallel processing tasks.

- Classical methods are less efficient in solving combinatorial optimization problems with considerable search space size when compared to metaheuristic methods. A major difficulty in combinatorial problems like in the case of traveling salesman and vehicle routing problems, is the fact that they are nondeterministic polynomial time or NP-complete. This means that the optimization algorithm needs excessive time that increases in polynomial order to guarantee optimality. The computation time burden led many researchers to accept metaheuristic methods as substitutes to the classical techniques that can generate near optimal solutions within a reasonable time frame.

The choice of which optimization methods one should use is completely reliant on the targeted problem at hand. Careful analysis of the nature of the objective function and constraints can narrow the search process to select the most suitable tool.

2.6 Summary

This chapter highlights the main components of optimization problems along with some basic definitions. An attempt to classify different types of optimization problems is made. Basic concepts of multi-objective optimization, Pareto dominance, and handling methods are illustrated. A discussion of different solution methods and differences among classical and non-classical methods are also addressed.

Chapter 3

Particle Swarm Optimization Theory and Development

3.1 Introduction

The fact that most optimization problems when modeled accurately are of non-convex and multimodal nature has encouraged many researchers to develop new optimization techniques to overcome such difficulties. PSO is one of the newly developed optimization techniques with many attractive features. Early experimentations of employing PSO in many applications in science and technology such as chip design and project crashing analysis, as can be seen in chapter 4 and partially at the end of this chapter, indicate its promising potential. Thus, the basics of PSO theory, development, and main features are presented in the following sections.

3.2 Fundamentals of Particle Swarm Optimization

Kennedy and Eberhart first introduced PSO in 1995 as a new metaheuristic method [22;23]. They studied a stochastic nonlinear model that was developed by Heppner and Grenander to simulate species movement traveling in groups [24]. The original objective of the research conducted by Heppner and Grenander was to create a computer model that simulates the social behavior of bird flocks and fish schools. As Kennedy and Eberhart progressed in their research, they discovered that with some modifications, the social behavior model can also serve as a powerful optimizer. They realized that such species try to approach their target in an optimal manner which resembles finding the optimal solution to any mathematical optimization problem. The first version of PSO was intended to handle only nonlinear continuous optimization problems.

A key attractive feature of the PSO approach is its simplicity as it involves only two model equations. In PSO, the coordinates of each particle represent a possible solution associated with two vectors, the position (x_i) and velocity (v_i) vectors. In N-dimensional search space, $X_i = [x_{i1}, x_{i2}, ..., x_{iN}]$ and $V_i = [v_{i1}, v_{i2}, ..., v_{iN}]$ are the two vectors associated with each particle *i*. A swarm consists of a number of particles "or possible solutions" that proceed (fly) through the feasible solution space to explore points where optimal solutions exist. During their search, particles interact with each other in a certain way as to optimize their search experience. In each iteration, the particle with the best solution shares its position coordinates (*gbest*) information with the rest of the swarm. Then, each particle updates its coordinates based on its own best search experience (*pbest*) and (*gbest*) according to the following equations:

$$v_i^{k+1} = v_i^k + c_1 r_1 (pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k) \tag{3.1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{3.2}$$

where

- c_1 and c_2 are two positive acceleration constants, they keep balance between the particle's individual and social behavior when they are set to be equal.
- r_1 and r_2 are two randomly generated numbers with a range of [0,1] added in the model to introduce stochastic nature to the particles' movement.
- $pbest_i^k$ is the best position particle *i* achieved based on its own experience; $pbest_i^k = [x_{i1}^{pbest}, x_{i2}^{pbest}, ..., x_{iN}^{pbest}]$
- $gbest^k$ is the best particle position based on overall swarm's experience; $gbest^k = [x_1^{gbest}, x_2^{gbest}, ..., x_N^{gbest}]$
- *k* is the iteration index

Equations (3.1) and (3.2) represent the original PSO model equations introduced in 1995. However, this model experienced poor convergence characteristics and sometimes additional fitness evaluations were needed to find an optimal solution.

3.3 PSO Development

Many advances in PSO development elevated its capabilities to handle a wider class of complex engineering and science optimization problems and to improve its overall performance. Summaries of recent advances in these areas are presented in references [25] and [26] and the discussion of these advances will be limited to the ones directly related to this thesis. Different variants of the PSO algorithm were proposed but the most standard is the global version of PSO (*Gbest* model) introduced by Shi and Eberhart [27], in which the whole population is considered as a single neighborhood throughout the optimization process. The original model Equations (3.1) and (3.2) are modified as follows:

$$v_i^{k+1} = \underbrace{wv_i^k}_{previous\ velocity} + \underbrace{c_1r_1(pbest_i^k - x_i^k)}_{cognitive\ component} + \underbrace{c_2r_2(gbest^k - x_i^k)}_{social\ component} \tag{3.3}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{3.4}$$

where

w is the inertia weight and it is a decreasing function of the iteration index;

$$w(k) = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{Max.\ Iter.}\right) \bullet k \tag{3.5}$$

The velocity vector in Equation (3.3) consists of three terms that determine the next position:

1. Previous velocity: This is the stored velocity from the previous iteration to regulate each particle from making severe changes in its direction between consecutive iterations.
2. The cognitive component: This term represents the attraction force that each particle has toward its best position achieved based on its own flying experience.
3. The social component: This term corresponds to each particle tendency to be attracted toward the best position discovered among the entire individuals in a swarm.

To maintain a good balance between the individuality and sociality, c_1 and c_2 are typically set to be equal. If c_1 is set greater than c_2, each particle individual performance will be weighed more in Equation (3.3) and it is more likely that the algorithm will get trapped in local solutions (i.e. the best solution achieved by that individual particle). On the contrary, if c_1 is set less than c_2, that algorithm might fail to converge. The inertia weight parameter introduced in Equation (3.3) allows the velocity vector to start with larger values, and then it decreases as the iteration index increases to limit any big particle movements towards the end of the optimization process. This modification improves the convergence characteristics significantly. Factors affecting the flying experience of each particle in its search for optimal solution are shown in Figure 3.1.

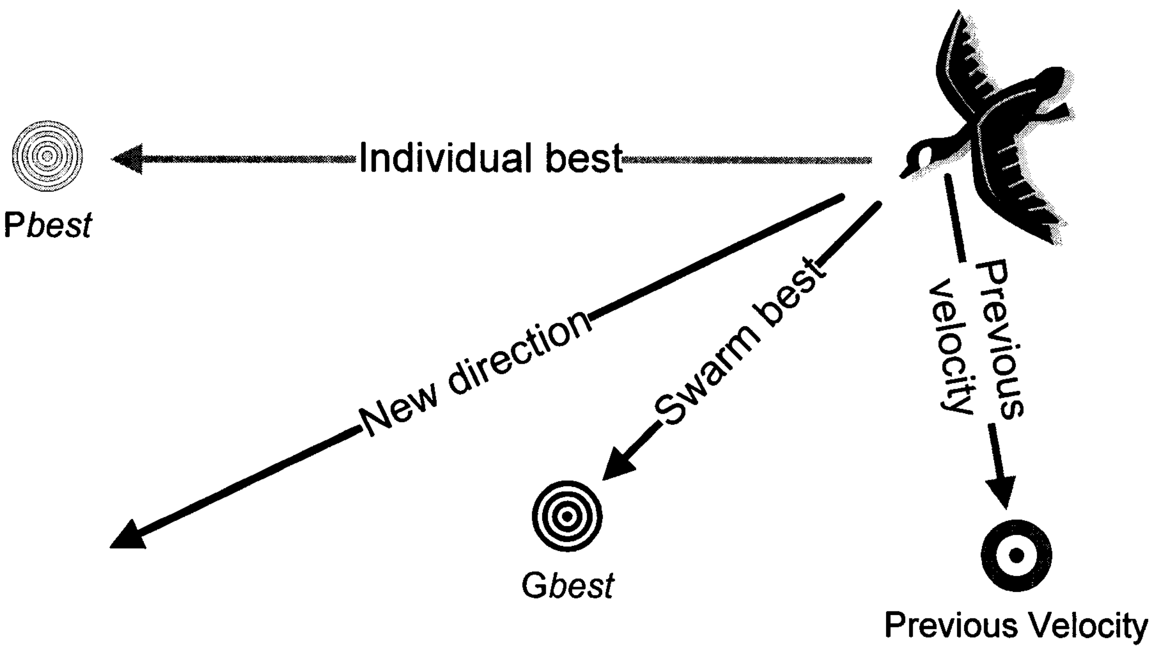

Figure 3.1. Influential elements on the particle's movement during its search for an optimum.

3.4 PSO Versus Other Optimization Techniques

PSO is a population-based evolutionary technique that has many key advantages over other optimization techniques, for example:

- It is a derivative-free algorithm unlike many conventional techniques.
- It has the flexibility to be integrated with other optimization techniques to form hybrid tools.
- It is less sensitive to the nature of the objective function, i.e. convexity or continuity.
- It has fewer parameters to adjust unlike many other competing evolutionary techniques.
- It has the ability to escape local minima.
- It is easy to implement and program with basic mathematical and logic operations.
- It can handle objective functions with stochastic nature like in the case of representing one of the optimization variables as random.
- It does not require a good initial solution to start its iteration process.

The PSO algorithm can be best described in general as follows:

1) For each particle, the position and velocity vectors will be randomly initialized with the same size as the problem dimension.
2) Measure the fitness of each particle (*pbest*) and store the particle with the best fitness (*gbest*) value.
3) Update velocity and position vectors according to Equations (3.3) and (3.4) for each particle.
4) Repeat steps 2-3 until a termination criterion is satisfied.

A pseudo-code of general PSO algorithm is shown in Figure 3.2.

```
Set the algorithm parameters;
For each particle
        Randomly initialize the position vector;
        Randomly initialize the velocity vector;
End
Measure the fitness of each particle;
Store pbest
Store gbest
While the stopping criteria is not met
        For each particle
                Update the velocity and position vectors
                Measure the fitness of the new position vector
                If the new fitness value is better than the previously stored one
                        Store the new position vector as pbest
                        Store the new fitness value
                End
        End
        Determine the particle with lowest fitness value in the search history
        and store its position vector as gbest
End
```

Figure 3.2. A pseudo-code of PSO algorithm.

As mentioned in chapter 2, in addition to traditional gradient-based optimization algorithms, there are many other heuristic techniques that compete with PSO such as genetic algorithms, simulated annealing, evolutionary programming, and most recently ant colony optimization. In general, most of these techniques can be used to solve various optimization problems in a similar way to the case of PSO. However, such competing techniques tend to have major drawbacks such as:

- More parameter tuning is required.
- They tend to require more computational time in most cases.
- Heavily involved programming skills are required to develop and modify competing algorithms to suit different classes of optimization problems.
- Some techniques require binary conversion instead of working with direct real valued variables.

- Most of them require a considerable number of population members that would translate to more fitness evaluations.

On the other hand, some advantages of the aforementioned algorithms over PSO are:

- The availability of commercial versions of some algorithms like Matlab (genetic algorithm and simulated annealing) and Excel premium solver (evolutionary programming).
- The extensive collection of books and research literature, especially in the case of genetic algorithm and evolutionary programming, that provide broad coverage of these competing methods.

Despite the simplicity of the PSO concept and implementation, its superiority is proven when compared with other techniques in many different application areas [28-33]. The following simple yet instructive example is developed for a numerical illustration of PSO global searching capabilities, the way it evolves to reach optimal solution, and to compare its performance to other popular optimization techniques.

Example 3.1:

Find the global solution to the following minimization problem:

$$F(x_1,x_2) = x_1 - x_2 - 5\sin(2x_1 + x_2) - \cos(3x_1 - x_2) + \sin(x_1 - x_2) - \cos(x_1 + x_2) \tag{3.6}$$

subject to

$$-5 \le x_1, x_2 \le 5 \tag{3.7}$$

There are multiple valleys and peaks in the shape of this function as depicted in Figure 3.3. This increases the chances of having any gradient based optimization technique trapped in a local optima. A PSO program was implemented in an attempt to locate the global minimizer of this objective. All PSO programs implemented in this thesis are written in Matlab 7 and simulations were performed utilizing an AMD Athlon 64 X2 Dual-Core processor with 2 GB of RAM under windows XP environment. To demonstrate the PSO consistency and robustness in finding the global optimal solution, the program executed 100 independent runs and the findings are tabulated in Table 3.1. It is clear that PSO was capable of detecting the global or near global solution in all cases.

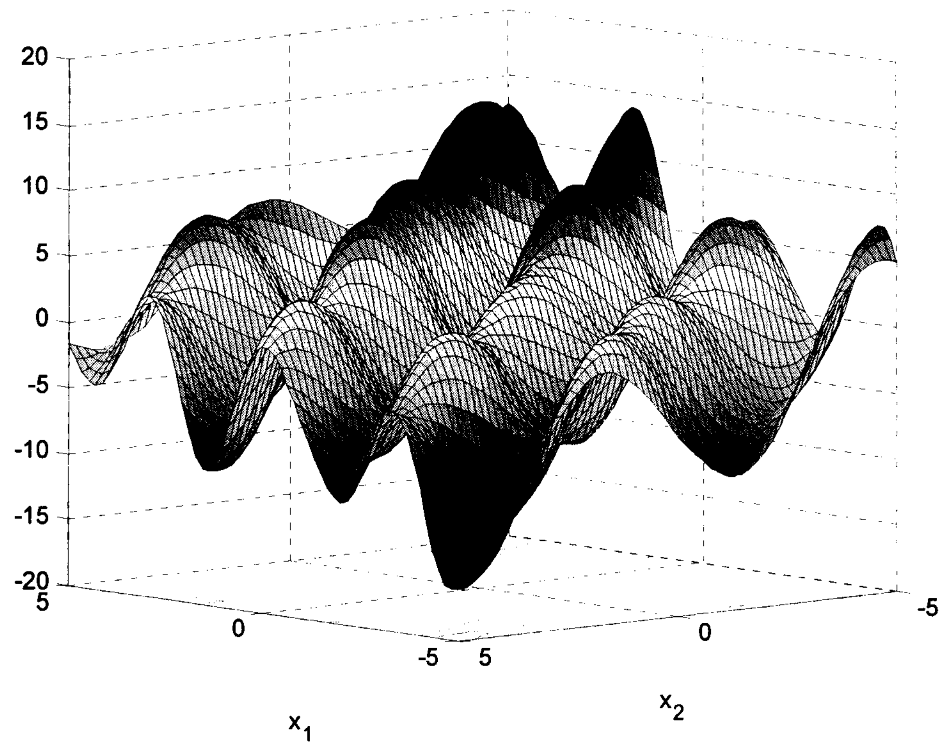

Figure 3.3. Shape of the objective function in Example 3.1.

Table 3.1. PSO Solution to Example 3.1

Solution		Objective			Average time (s)
x_1	x_2	Mean	Best	Worse	
-4.7119	4.7116	-16.4247	-16.4248	-16.4216	0.0205

An interesting and unique feature that exists in the PSO is the population clustering around the global solution. In other evolutionary algorithms like genetic algorithms, only one individual among the population usually reaches the optimal solution. In contrast, the population in the PSO are initially scattered at random in the feasible search space then they start clustering as they evolve in their search experience. This clustering phenomenon is illustrated in Figures 3.4-3.9 for this example. The figures show snap shots of the particles' journey in their search for global optimum for this objective.

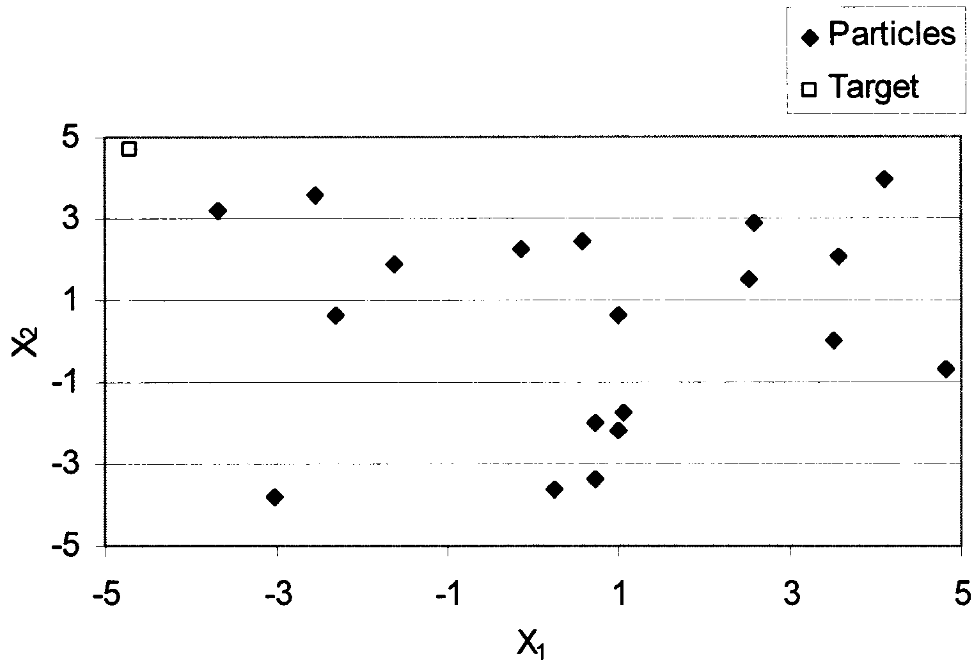

Figure 3.4. Initial particles distribution in the feasible search space.

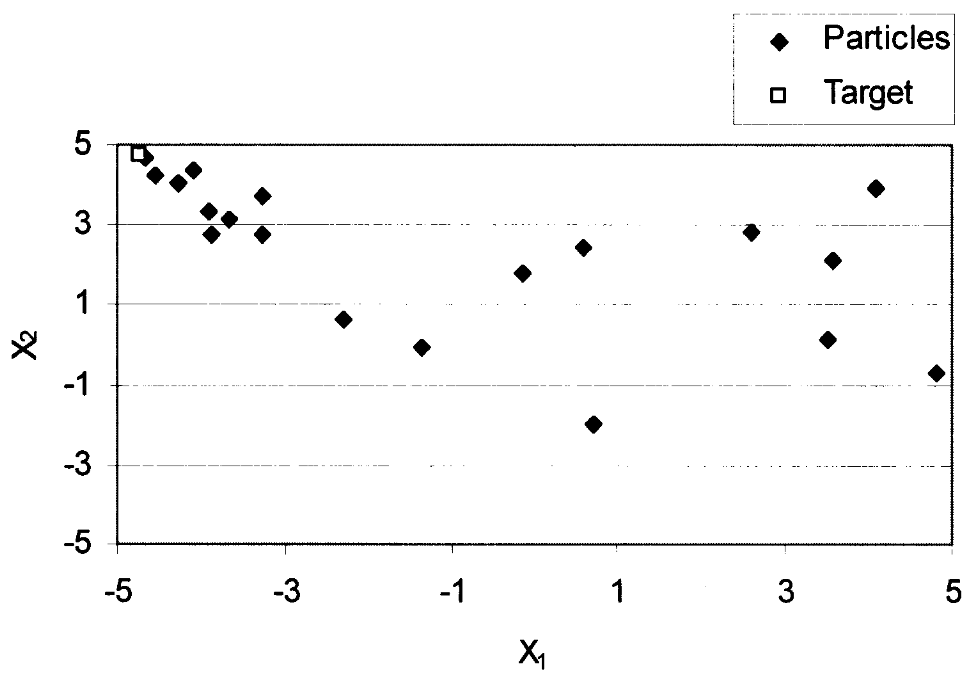

Figure 3.5. Particles distribution at iteration 25.

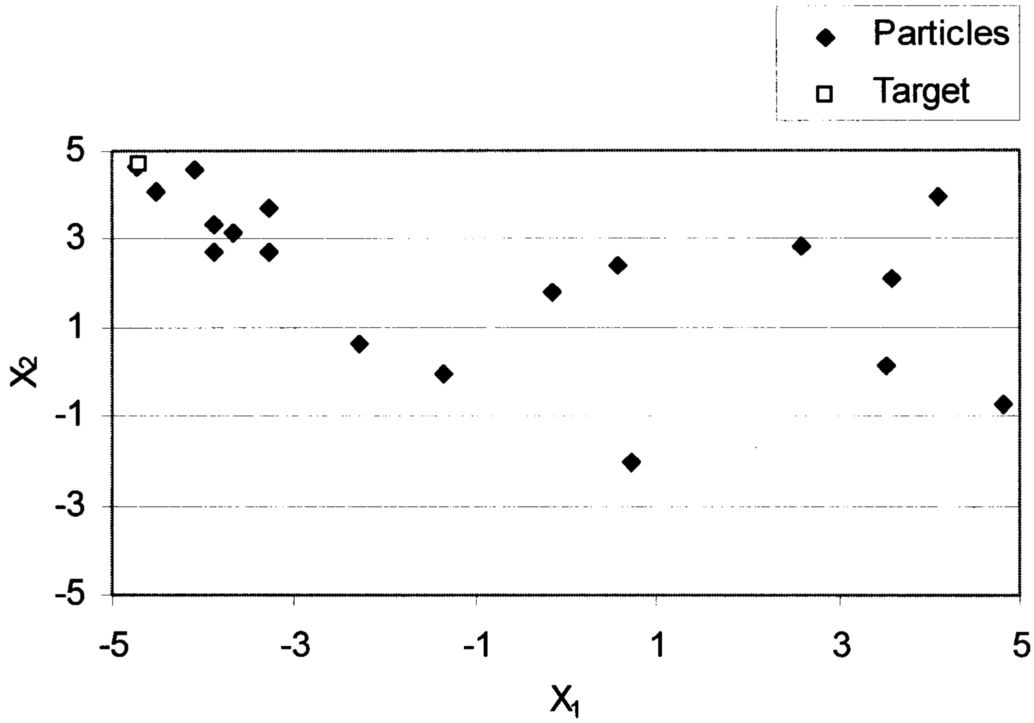

Figure 3.6. Particles distribution at iteration 50.

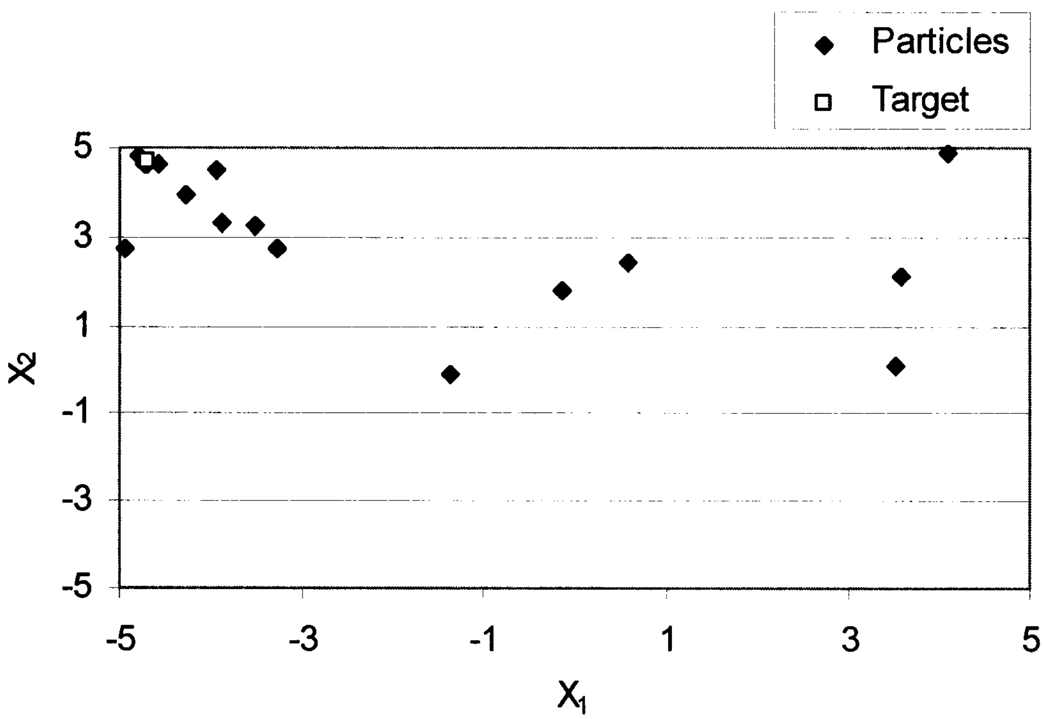

Figure 3.7. Particles distribution at iteration 75.

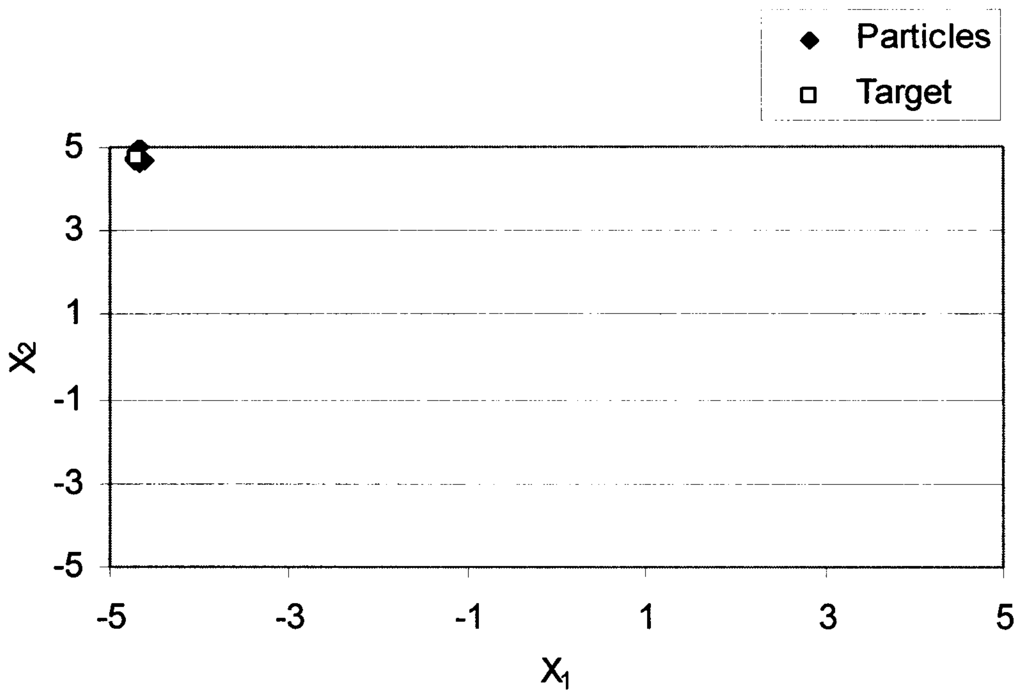

Figure 3.8. Particles distribution at iteration 100.

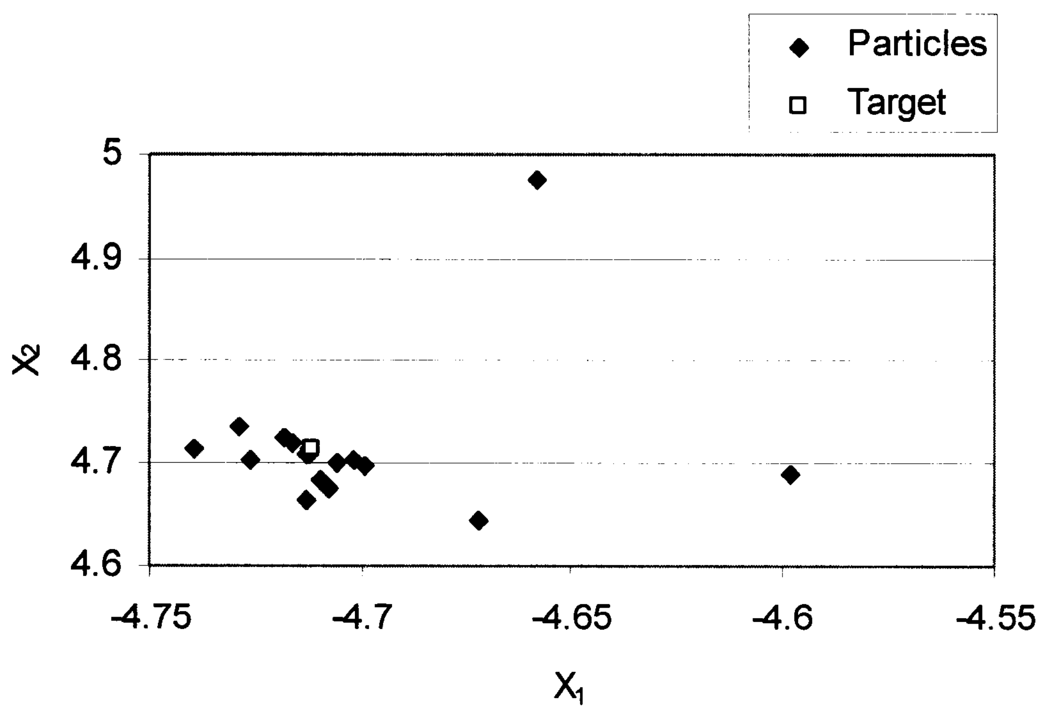

Figure 3.9. Close up of particles distribution at iteration 100.

To emphasize PSO global search capabilities and to compare its performance with other optimization methods, the solution to the simple problem in Example 3.1 was obtained using various methods as shown in Table 3.2. The other competing methods are as follows:

1. Excel premium solver: This additional excel add-in developed by Frontline Systems, Inc. extends the basic solver capabilities that come pre-installed with Microsoft Excel package [34]. There are two main nonlinear optimization techniques in this package:
   - Enhanced GRG.
   - Standard Evolutionary.

   As the results in Table 3.2 indicate, the GRG approach was able to solve the problem only when the solution was initialized in the neighborhood of the global solution. It converged to multiple local solutions when it started in the wrong valley and even got stuck at the problem boundary in one case when it was started at the solution space border. The evolutionary algorithm performed better in solving this non-convex optimization problem.
2. Matlab optimization toolbox [35]: SQP is the main algorithm used to solve constrained nonlinear optimization problems in Matlab. Similar to the GRG performance, the SQP algorithm converged to the global solution only when it was initialized in the vicinity of the targeted area.
3. LINGO: This premier optimization software has multiple built-in solvers with global searching capabilities [36]. The main nonlinear solver is based on the GRG approach and it automates the initialization process. Unfortunately, the algorithm converged to a local point and failed to reach the global optimum. The same point trapped the SQP algorithm at two different initialization points.

This example shows how the concept of non-convexity can create a challenging environment to most derivative-based approach methods. It also shows some aspects of the superiority of the new metaheuristic methods in handling objectives with non-convex natures. It may be easy to perform trial and error experiments to rule out the fruitless regions in the solution hyperspace in case of problems with a few variables like in this example. However, many real world problems tend to have more than a few variables in which this process can no longer be practical.

Table 3.2. Comparison of Different Solution Methods for Example 3.1

Computing Environment	Solution Technique	Initial Guess		Solution		Objective	Version
		X_1	X_2	X_1	X_2		
Excel	GRG	0	0	0.15375	1.22458	-7.85850	Premium Solver V5.0
Excel	GRG	5	5	4.31411	5.00000	-4.60343	
Excel	GRG	-5	-5	-5.00000	-5.00000	4.92958	
Excel	GRG	2.5	-2.5	1.57080	-1.57079	-3.85841	
Excel	GRG	**-2.5**	**2.5**	**-4.71239**	**4.71239**	**-16.42478**	
Excel	Evolutionary	**0**	**0**	**-4.71240**	**4.71258**	**-16.42478**	
Matlab	SQP	0	0	1.57080	4.71239	-10.14159	V7.1.0(R14) SP3 Optimization Toolbox 3.0.3
Matlab	SQP	5	5	1.57084	4.71222	-10.14159	
Matlab	SQP	-5	-5	-5.00000	-5.00000	4.92958	
Matlab	SQP	2.5	-2.5	1.57080	-1.57080	-3.85841	
Matlab	SQP	-2.5	2.5	-4.71239	-1.57080	-10.14159	
Matlab	SQP	**-3.5**	**3.5**	**-4.71241**	**4.71242**	**-16.42478**	
LINGO	GRG	NA	NA	1.57080	4.71239	-10.14159	LINGO 10.0
Matlab	PSO	**random**	**random**	**-4.71190**	**4.71160**	**-16.42478**	NA

Other heuristic techniques that belong to the same category are summarized in [37]. These techniques have been gaining more popularity mainly because of their robustness, simplicity, and their ability to deal with more exact models instead of making intolerable approximations. The major drawbacks of PSO are the lack of solid mathematical background and failure to theoretically assure global optimal solutions, just like in the case of other metaheuristic optimizers. PSO has been proven to perform well in many standard benchmark optimization problems used by researchers to validate new global optimization techniques [38-41]. Reference [39] is an excellent reference that analyzed and studied the PSO promising convergence characteristics. In [39], Clerc and Kennedy successfully established some mathematical foundations to explain the behavior of a simplified PSO model in its search for an optimal solution. However, further analysis is needed to explain other issues of the PSO like the social influence aspect of the algorithm and generalized rules in how to tune its parameters to suit different optimization problems. In [39], the authors emphasized the need for further future studies by stating "Several kinds of coefficient adjustments are suggested in the present paper, but we have barely scratched the surface and plenty of experiments should be prompted by these findings." Figure 3.10 shows the exponentially increasing growth in various research areas with regard to PSO (based on IEEE/IEE databases).

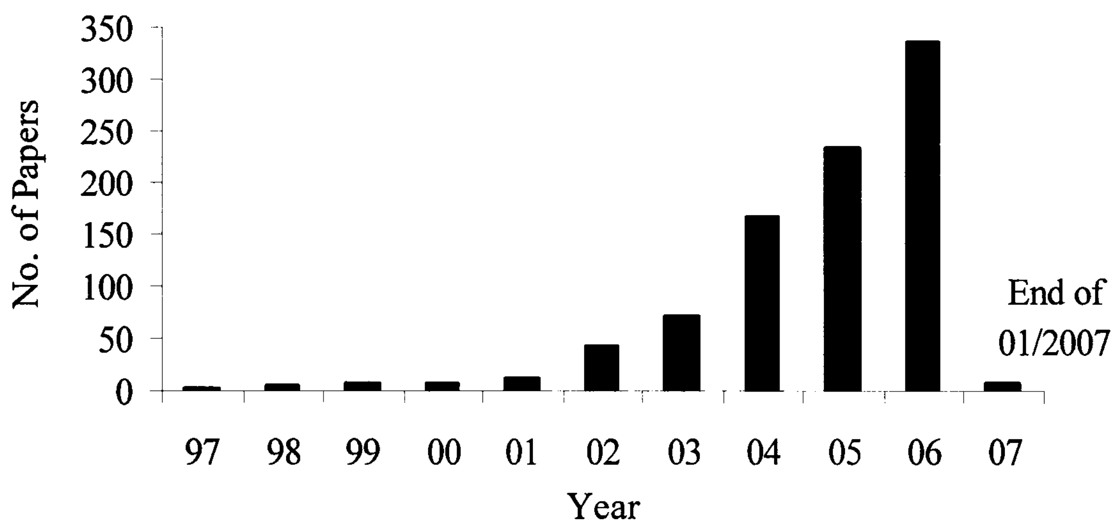

Figure 3.10. Number of PSO related journal and/or conference papers each year in all research fields.

3.5 Constraint Handling Methods in Evolutionary Algorithms

There are different ways to handle constraints in evolutionary computation optimization algorithms just like in the case of the PSO. The following constraint handling methods are the most commonly used [40]:

1. Preserving feasible solution method: In this method, solutions are initially placed in the feasible search space and remain within this space by adapting an update mechanism that generates only feasible solutions.
2. Infeasible solution rejection method: This approach rejects any solution that violates the feasible search space.

3. Penalty function method: In which a penalty factor is added to the objective once any constraint violation occurs. It transforms the constrained optimization problem to unconstrained one.
4. Solution repair method: This approach converts the infeasible solution to a feasible one by performing special operations.

Selecting the proper constraint handling method is highly reliant on the nature of the problem. Reference [40] indicates that in the solution repair method, the process of reinstating the infeasible solution to a feasible one can be as challenging as solving the original problem. In the penalty function method, the objective function is augmented by adding penalty terms to transform the constrained problem into an unconstrained one. This approach usually encounters a major difficulty in how to properly select penalty factor values. If the penalty factors selected are high, the optimization algorithm will get trapped in local solutions. On the other hand, the algorithm may not be able to detect a feasible solution if the penalty factors are low [42].

3.6 Real World Applications of Recent Metaheuristic Methods

The appealing features that exist in metaheuristic methods have led to enormous utilizations of these methods to real world applications. The mature metaheuristic methods like genetic algorithms, simulated annealing, evolutionary programming, and neural networks have been applied to an abundant number of applications and they are recognized as well established methods. Even more, they became standard options in many common optimization software programs like in the case of the new release of Matlab (genetic algorithms, simulated annealing, and neural networks are presently available options) and the Excel premium solver (the evolutionary programming option is available). Thus, the focus of this section is to briefly summarize new real world applications of the most recent metaheuristic methods, i.e. PSO and ant colony optimization.

3.6.1 PSO Real World Applications

The following is a list of recent PSO real world applications in different fields:

1. Auto2Fit software: CPC-X Software Inc. developed a commercial data analysis program that incorporates multiple versions of PSO as one of the available optimization tools available to solve complex optimization problems. This software is designed specifically for regression and curve fitting, global optimization, model auto-calibration, and equation solving [43].
2. Human tremor classification: A neural network was constructed to intelligently distinguish between a normal physiologic tremor and a pathologic tremor (Parkinson's disease). The PSO was used to evolve the neural network to its optimal settings in order to increase its pattern recognition accuracy. Results indicate that the PSO-based neural network reached 100% accuracy on all the 22 patterns used to validate the classification process [13].
3. Design of aperiodic antenna arrays: In this application, various versions of PSO were utilized to develop an enhanced antenna array design. The antenna arrays were fabricated and testing results indicated the effectiveness of the PSO-based design performance [44].
4. Chip design: Reference [45] appears to be the first to present a PSO-based chip design of reconfigurable sensor signal amplifier. PSO is used to find the optimal settings of analog structures in a dynamically reconfigurable multi-cell chip.
5. Project crashing analysis: PSO was employed to find the optimal resources allocation strategy for a construction project that rehabilitates 8 km of an existing highway. It reduced the project execution time at relatively low additional cost [46].

3.6.2 Ant Colony Optimization Real World Applications

Reference [47] pointed out some real world applications of ant colony optimization and they are summarized as follows:

1. EuroBios, a worldwide software vendor, employed ant algorithms to various optimization problems like the routing/scheduling of airplane flights, supply chain networks, and telecommunication networks [48].
2. AntOptima, a Swiss company, developed a set of optimization tools based on ant colony optimization theory for logistics providers to efficiently run their fleet [49]. The main users of their products are:
   - Pina Petroli: A Swiss heating oil distribution company.
   - Migros: The main Swiss supermarket chain.
   - Barilla: The main Italian pasta maker.
3. BiosGroup: Another vehicle routing application for a French company was developed by this company that is based on ant colony optimization theory [50].

3.7 Summary

This chapter covers the basics behind PSO theory and recent developments that have been made to enhance its overall performance. Differences between PSO and other optimization techniques are addressed. A numerical example is derived to illustrate the promising capabilities of PSO in solving optimization problems with multimodal characteristics. A comparison of PSO performance against other various optimization techniques is made. Some real world applications of recent metaheuristic tools are presented to signify their promising potential and competence. Future PSO development is anticipated to mainly focus on the theoretical investigations of the global convergence characteristics, hybridization with other optimization techniques, multi-objective optimization, and employment in new applications.

Chapter 4

Literature Review

4.1 Introduction

This chapter presents a review of the most recent publications with regard to different areas directly related to the research work conducted in this thesis. To establish a solid foundation and understanding of the scope of this thesis, the literature review is divided into three main sections as follows:

1. PSO Applications in Electric Power Systems: This part covers most PSO applications in different areas of electric power systems with added emphasis on the electric power dispatch and OPF problems. Coverage is presented based on the research area of interest.
2. EED: This part reviews most published articles that address both emission and economic dispatching issues simultaneously.
3. OPF: This section addresses recent developments in methods of solving the OPF problem.

4.2 PSO Applications in Electric Power Systems

The focus of the present section is to survey and summarize most PSO applications in the area of electric power systems. This work can serve as a good starting point for those interested in learning about the development of PSO and its applications in electric power systems engineering. Research in power systems has its own share in applying PSO to various optimization problems. Figure 4.1 shows the number of published papers in which PSO was applied to different areas of electric power systems (based on IEEE/IEE/Elsevier databases). It clearly indicates its applicability and the fast growing interest in PSO utilization in this research area.

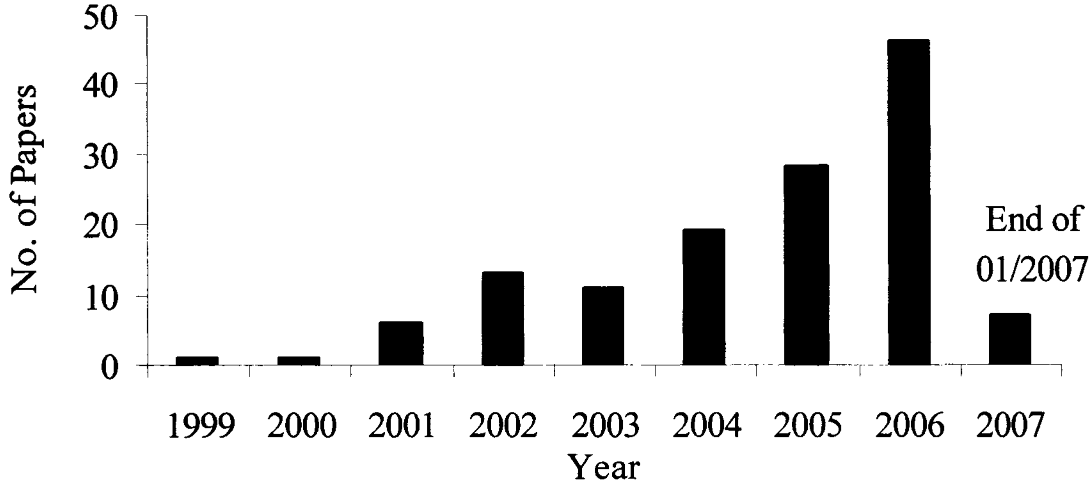

Figure 4.1. Number of PSO related published papers each year in power system areas.

Electric power system optimization problems are fairly diverse and they can be categorized in terms of the objective function characteristics and/or type of constraints. They are commonly referred to as linear, nonlinear, integer, and/or mixed integer constrained optimization problems. PSO applications in electric power systems are similar to those in different research fields once a common formulation is established. However, PSO parameter tuning might be different from one application to another.

Reference [51] appears to be the first to apply PSO in the area of electric power systems to minimize the real power losses of an electric power grid. The problem is classified as one of mixed-integer nonlinear optimization because some control variables are continuous while others are discrete. This introductory application was followed by a series of PSO related papers to solve similar problems [52-54]. The initial motivation to apply PSO in this research field is mainly due to the complexity of this problem since power flow calculations that involve solving a system of nonlinear equations of the power system at one point in time, are required to evaluate each solution candidate. The PSO technique demonstrated its effectiveness in solving this difficult optimization problem by improving the solution's accuracy and computation time. The following are the major areas in which PSO was applied:

1. **Economic Dispatch:**

El-Gallad *et al.* [55] and Park *et al.* [31] adapted PSO to solve the traditional economic dispatch problem. In both papers, the objective function was formulated as a combination of piecewise quadratic cost functions with non-differential regions instead of using a single convex function for each generating unit. This innovation in problem formulation is due to the incorporation of practical operating conditions like valve-point effects and different fuel types. The system constraints included in reference [55] were system demand balance constraint with network losses incorporated and the generating capacity limits. Park *et al.* did not account for transmission line losses in reference [31] for simplicity. El-Gallad *et al.* added new constraints to the problem formulation in reference [56] by introducing system spinning reserve and generator prohibited operating zones. In this formulation, they included the same constraints as those used in reference [55] and considered a single convex cost function.

In reference [28], a different formulation was proposed by including the generator ramp rate limits in the same problem treated in [56]. In Gaing's work [28], a comparison is made between PSO and genetic algorithm performance in solving the same economic dispatch problem. Gaing introduced a dynamic aspect to the same problem by adding a time-varying system load in addition to accounting for some of the generator operation related restrictions, such as ramping rate limits and prohibited operating zones, while imposing system spinning reserve requirements and line flows as inequality constraints [57]. Victoire and Jeyakumar extended Gaing's research by forming a hybrid optimizer to tackle the same problem [58]. They used SQP to fine-tune PSO search in finding the optimal solution.

Kumar *et al.* included emission aspects of the power dispatching problem [59]. They utilized PSO in solving a multi-objective optimization problem that included both cost and emission functions. They combined the two objective functions by assigning a single price penalty factor to the emission function to form a single objective function. Reference [60] presents improved versions of PSO to solve both convex and non-convex economic dispatch problems that take into account different operational constraints. The main contributions of the proposed approaches are the integration of local random search with PSO and the splitting up of the cognitive term such that both the best and worse particle positions affect the velocity update equation. Wang and Singh formulated a multi-objective emission-economic dispatch problem for a multi-area system [61]. A PSO approach was developed to solve the problem with convex objective functions while accounting for the tie-line transfer limits as additional constraints. Reference [62] presents a hybrid form of PSO and evolutionary programming to solve the economic dispatch while accounting for the valve point loading effects. The hybrid approach showed faster convergence characteristics when compared to the conventional PSO or evolutionary programming.

2. Reactive Power Control and Power Loss Reduction:

In this area, PSO was used to optimize the reactive power flow in the power system network to minimize real power system losses. Yoshida *et al.* [51;52;54] and Fukuyama *et al.* [53] took the initiative of introducing PSO to reactive power optimization. In their problem formulation, the objective was to find the optimal settings of some control variables that would minimize the total real power losses in a network. The control variables were automatic voltage regulator operating values, transformer tap positions, and a number of reactive power compensation equipment subject to equality and inequality constraints. Based on the nature of the control variables, the problem was classified as a mixed-integer nonlinear optimization problem since some variables are continuous while others are discrete. Mantawy and Al-Ghamdi investigated the same problem using a different test system [63].

Miranda and Fonseco appear to be the first to introduce a hybrid PSO approach in this area [64;65]. They combined evolutionary strategies with PSO to improve the robustness of the classical PSO. In reference [66], Zhao *et al.* combined multi-agent systems with PSO to solve the same problem. Esmin *et al.* considered shunt capacitor banks as the only type of control variables in their problem formulation [67]. They incorporated the tangent vector technique to identify the critical area of power system network where voltage stability might be in danger. Then they applied PSO to find the "needed" reactive power compensation. A new hybrid method was introduced by Chuanwen and Bompard as they combined PSO with a linear interior point technique to solve a reactive power optimization problem [68]. In their work PSO was used as a global optimizer to search the entire solution space while the linear interior point method acted as a local optimizer to search the space around the optimal solution.

To show the effectiveness of PSO in reactive power control and power loss reduction, it was successfully applied to a practical power system in the province of Heilongjiang in China [32]. This system consists of 151 buses and 220 transmission lines with 71 control variables. A different problem formulation was proposed by Coath *et al.* where they considered reactive power loss minimization as an objective function [69]. They also introduced generator real power outputs as additional control variables. The difference in their problem formulation was mainly due to the inclusion of wind farms as modern integral parts of the power system networks.

3. OPF:

Abido is credited with introducing PSO to solve the OPF problem [70]. In OPF, the goal is to find the optimal settings of the control variables such that the sum of all the generator's cost functions is minimized. The generator real power outputs are considered control variables in addition to the other control variables considered previously in reactive power optimization problems. PSO was effective in dealing with this complex optimization problem that has various equality and inequality constraints and both continuous and discrete variables. In a different approach to the problem, Zhao *et al.* solved the highly constrained OPF optimization problem by minimizing a non-stationary multi-agent assignment penalty function [29]. In this formulation, PSO was used to solve the highly constrained OPF optimization problem in which the penalty values were dynamically modified in accordance with system constraints. In reference [71], the passive congregation concept was incorporated in PSO to solve the OPF problem. This hybrid technique improved the convergence characteristics over the traditional PSO in solving the same OPF problem. Wang *et al.* developed a modified PSO to solve the OPF problem with the objective being the minimization of the quadratic fuel cost function [72]. The proposed algorithm mainly relied on the idea of randomly exchanging information among the entire swarm rather than only the best member in the swarm. The environmental-economic transaction planning problem in the electricity market was formulated as a multi-objective OPF in reference [73]. A multi-objective PSO algorithm was developed to solve the problem via a non-stationary multi-stage assignment penalty function. Different versions of PSO were developed in reference [74] in an attempt to construct a comparison of their performance with regard to the OPF. The objective functions selected in this study were the real power losses and voltage profile improvement. Gaing introduced an enhanced PSO to solve a multi-objective OPF problem with the objective functions being the fuel cost, real power losses, and voltage deviation [75].

4. Power System Controller Design:

In references [76] and [77], PSO was employed to find the optimal settings of power system stabilizer parameters. The problem was formulated as one of min-max optimization of two eigenvalue-based objective functions. Okada *et al.* went along the same lines when they used PSO to optimally design a fixed-structure controller to enhance the stability of power systems [78]. In this work, the authors' goal was to find the global optimal solution of a multimodal optimization problem. PSO was also used in optimizing the feedback controller gains. Al-Musabi *et al.* made use of PSO in finding optimal controller gain values for a load frequency problem of a single area power system [79]. Abdel-Magid and Abido extended PSO usage in this area when they enlarged the control system to two areas [80]. In their work, they considered two types of controllers namely an integral controller and a proportional plus integral controller. Juang and Lu combined the genetic algorithm with PSO in reference [81] to perform the same optimization process as in [80] on a fuzzy proportional-integral-controller. Ghoshal augmented the problem by trying to find the optimal proportional-integral-derivative controller gains of a three area power system [82]. He tackled the problem using PSO in addition to other heuristic techniques. Lu and Juang applied PSO to design a fuzzy controller for a thyristor-controlled series capacitor to enhance the transient stability of flexible alternating current transmission systems (FACTS) [83].

5. Neural Network Training:

Neural Networks emerged as a valuable artificial intelligence tool in many areas of electric power systems. El-Gallad *et al.* used PSO to train a neural network for power transformer protection [84]. The objective was to develop a model that would be able to intelligently distinguish between magnetizing inrush current and internal fault current in power transformers. PSO was employed to improve the accuracy and the execution time of the identification process. Hirata *et al.* used PSO to determine the optimal connection weights of a neural network model used to improve stability control of power systems [85]. They formulated the optimization problem as a min-max problem with an objective function that has non-differential and discontinuous nature. Kassabalidis *et al.* integrated PSO with a neural network to identify the dynamic security border of power systems under a deregulated power system environment [86].

6. Other Electric Power System Areas:

In [87] and [88], the performance of PSO was explored in the area of electric power quality by improving the process of feeder reconfiguration. The problem was formulated as a nonlinear optimization problem with non-differentiable characteristics.

Victoire and Jeyakumar combined PSO, sequential-quadratic-programming, and tabu-search to form a hybrid technique to solve the unit commitment combinatorial optimization problem [89]. In the area of short-term load forecasting, Huang *et al.* were able to identify the autoregressive moving with the exogenous variable model using PSO [30]. Slochanal *et al.* and Kannan *et al.* introduced PSO in the area of generation expansion planning in references [90] and [91] to solve discrete nonlinear optimization problems. They used it in [90] to maximize the profit of a generating utility subject to certain market conditions and various system constraints. In [91], PSO was employed to minimize the capital and operation cost of the generation expansion planning problem. Also in this area, PSO was utilized in solving the expansion planning problem of a transmission line network [92].

Koay and Srinivasan solved the multi-objective generator maintenance scheduling problem by creating a hybrid technique by means of combining PSO with evolutionary strategies in reference [93]. In power system reliability studies, PSO was applied to feeder-switch relocation problems in a radial distribution system [94]. The authors in reference [94] used PSO to allocate the most appropriate positions to place sectionalized devices in distribution lines. The objective function of this problem is categorized as nonlinear with non-differentiable characteristics. In reference [95], applications of PSO in finding optimal operation settings of a system composed of distributed generators and energy storage systems were illustrated. Naka *et al.* and Fukuyama formed hybrid techniques by combining PSO with other heuristic techniques to improve the performance of a distribution of state estimator in [96] and [97] respectively. PSO was later applied to solve short term hydroelectric system scheduling problems in reference [98]. The problems in references [96-98] are formulated as continuous nonlinear optimization problems. Yu *et al.* applied PSO to tackle the discrete optimal capacitor placement problem in a noisy environment [99].

4.3 Survey of the Economic-Emission Dispatch

This section offers a general recent review of most research work conducted in the area of EED. Due to the rich volume of reported related articles, the discussion is limited to the scholarly work that handles both economic and emission dispatches in the same formulation. Reviewed papers are extracted exclusively from the IEEE database and categorized based on the solution method as follows:

1. **Classical Methods:**

Nanda *et al.* solved the EED problem using linear and nonlinear goal programming techniques for different types of fuel [7]. They used the least square minimization principle to linearize the quadratic cost and emission functions. However, the two objectives were treated separately and network losses were ignored in their formulation. Ramanathan proposed two methods to include the emission aspects as constraints to the classical economic dispatch, namely the efficient weights estimation technique and the partial closed form technique [100]. In the first method, the Kuhn-Tucker optimality condition is used to find the appropriate conversion factors to combine emission and cost functions. In the second method, the author derived a closed form solution to the economic dispatch with some simplifying assumptions. In reference [101], the problem was solved by considering the cost as a primary objective and the emission was treated as a bounded constraint with linear and nonlinear formulations. A comparison between the results of linear and nonlinear programming methods was presented with a conclusion in favor of the nonlinear approach. The authors used successive quadratic programming to solve the combined nonlinear programming problem. Lakshminarasimman *et al.* used multiple price factors to combine the two objectives based on the system constraints [102]. Then, they developed a closed loop approach, i.e. non-iterative, to solve the problem. Joshi and Patel approached the problem by considering the fuel cost as the main objective and included emissions as constraints in their formulation [103]. They employed Powell's method to convert the constrained problem into unconstrained one. In addition, they adapted goal programming to permit only feasible solutions under any operating condition. Muralidharan *et al.* employed adaptive dynamic programming technique to solve the EED problem [104]. In their approach, the problem was solved by decomposing the multistage decision problem into a sequence of single stage decision problems. This decomposition tends to simplify the process of obtaining the solution to the original problem. Lamont and Obessis introduced different emission models to account for start-up operations of thermal plants that was previously not accounted for [105]. The authors employed Kuhn-Tucker optimality conditions to minimize the fuel cost while treating different emissions as constraints. In a rather interesting and more practical study, Vickers *et al.* proposed a model that accounts for the impacts of the Clean Air Act Amendments that were enacted in 1990 to limit the emission of electric power utilities in the United States [106]. This law assigns an allowance, i.e. a specific number of permissible tons of emissions per year that each generating unit within a utility can produce, that should not be exceeded to improve air quality. The utility has the right to consume, sell, buy, transfer, or retain their given emission allowances. The developed model optimizes a cost function that includes fuel cost, sulfur removal cost, inventory cost, operation and maintenance cost, and allowance market cost subject to various operational constraints like emissions, fuel supply, fuel inventory, fuel transfer, generating units limits, and demand. It was designed for an American power company with a model consisting of 14,108 decision variables and 5,249 constraints. Linear programming was employed to solve this practical case. Along the same line, El-keib *et al.* employed the Lagrangian relaxation method to solve the EED problem with two different formulations while considering the impact from the same law [107].

All of the above attempts were able to find a single non-dominated solution based on the price, conversion factor, emission bounds, or weight factors of the overall multi-objective problem. The authors in reference [108] introduced the line flow constraints to the EED problem. They used a weighting method to aggregate the conflicting objectives and they applied the Lagrangian multiplier method to solve the problem with different weights considered. This approach successfully computed a full set of non-dominated solutions. Heslin and Hobbs developed a long term model to solve the EED problem that accounts for more complex features of power systems like planned outages, units with energy limitations like hydro plants and pump storage, and must run units that serve the base load [109]. In addition to the fuel cost and emissions, they included a new objective that reflects the cost of coalfield job losses as a result of changing coal to fuel with fewer pollutants. Since the model was developed for long term planning, they incorporated a probabilistic means to account for the variable cost of fuels. The three objectives were converted into a scalar objective by using the weighting method and the problem was solved using linear programming. They applied their model to the Ohio generation system and tradeoff curves were constructed successfully.

2. Artificial Neural Network:

Hopfield neural networks were utilized in reference [110] to solve the bi-objective optimization problem. A price penalty factor was used to combine the two objectives that yielded a single optimal solution to the problem. Kumarappan *et al.* solved the EED problem by adapting back propagation artificial neural network approach [111]. They used the participation factor method to optimally distribute the network losses among different generating units. Again, they used the price factor to convert the emission function into a financial quantity in order to combine it with the fuel cost function. Kar *et al.* provided a more in depth study of the parameter effects on the neural network performance in terms of solution accuracy and computation time with regard to the EED problem [112]. Their developed network was tested under various loading conditions and they reported that it was 10-12 times faster than the conventional method once enough training is conducted. However, the network was tested to solve the EED under a single price factor scenario. The authors in reference [113] used the weighting method to merge the two objectives into a scalar function. Network losses were ignored and a complete set of Pareto optimal solutions was obtained by varying the weights assignments. King *et al.*

used the weighting method to combine different objectives into one while accounting for losses [114].

In a more advanced implementation of neural network applications to solve the EED problem, Huang and Huang attempted to solve the problem using the abductive reasoning network approach [115]. Their approach involved the construction of a polynomial neural network with advanced statistical tools, based on the provided training data, to generate Pareto front. They adapted a fuzzy satisfaction-maximizing approach to sequentially adjust the weights of the conflicting objectives. The convergence stability performance of this complex network outperformed the conventional neural network when considering larger systems. Chen and Huang extended the use of polynomial network with their statistical features to develop an adaptive neural network to investigate its potential to solve the EED problem [116]. They used the goal attainment method to assign desired values for each objective in order to coordinate the competing objectives. The proposed approach was tested on two test systems under different load profiles and its performance was compared to conventional neural networks.

3. **Genetic Algorithms-Based Approach:**

Song *el al.* used a genetic algorithm to solve the EED problem with fuel switching incorporated into the problem as an additional constraint [117]. In their formulation, the emission function was treated as inequality constraint and included in the fitness function along with power balance equality constraint. In a similar formulation, Wang and Li adapted a genetic algorithm to minimize the wheeling cost of the transmission network and the fuel cost while imposing emission as an additional constraint to the problem [118]. A Tabu search algorithm was integrated within the genetic algorithm to form a hybrid tool to solve the EED problem in reference [119]. This hybridization reduced the likelihood of having the proposed algorithm getting trapped in a local optimum or premature convergence. The fuel cost and emissions were combined into a scalar objective by means of the price penalty factor while considering prohibited zones of the generating units. Venkatesh *et al.* introduced a new way to compute a price penalty factor that combines fuel cost and emissions into a single objective [120]. Then, the performance of genetic algorithm, micro genetic algorithm, and evolutionary programming was compared in solving the EED problem of different test systems with line flow constraints included. Reference [121] addresses power exchanges and stability issues of multi-area power systems with regard to the EED problem. The weighting method was used to reduce the multi-objectives into one and the genetic algorithm served as an optimizer to the problem under consideration. All the proposed approaches discussed above generated a single non-dominated solution, which gave no additional information about the shape of the Pareto front.

Tsoi *et al.* presented a study about the impacts of different fuel types and pollutants on tradeoff curves between the fuel cost and emissions [122]. Two hybrid algorithms were developed and were based on combining simulated annealing with an incremental genetic algorithm, a variant of the genetic algorithm that adapts different mechanisms to generate new chromosomes in order to enhance some of the shortcomings of the conventional genetic algorithm. Thenmozhi and Mary developed a two level genetic algorithm based approach to solve the EED problem [123]. In a recent development, Liu *et al.* developed a new genetic algorithm that mimics biological immune systems to solve the aforementioned problem [124]. In references [122-124], the Pareto optimal solution set was obtained by varying the relative weights of the competing objectives.

In a new innovative approach, Abido solved the EED problem by developing a non-dominated sorting genetic algorithm (NSGA) based approach to capture Pareto front [125]. He proposed a diversity preserving mechanism to overcome premature convergence and to provide a well distributed set of non-dominated solutions. A comparison of sharing techniques based on parameter space and objective space concluded that the latter method produced better diversity of Pareto optimal sets. The same author extended the capabilities of a real coded genetic algorithm to develop a strength Pareto evolutionary algorithm (SPEA) to solve the EED problem [8]. In this implementation, he developed a fuzzy based approach to extract the best compromise solution out of the entire set of Pareto optimal sets. Additionally, Abido proposed a niched Pareto genetic algorithm (NPGA), along with NSGA and SPEA, that has a built-in feasibility check to enforce only feasible solutions in an attempt to tackle the multi-objective problem [126]. More elaborate testing of three evolutionary computation methods namely NPGA, NSGA, and SPEA with regard to the EED problem was presented in reference [127]. A hybrid tool that combines simulated annealing in generating the selection process of the genetic algorithm was proposed by Das and Patvardhan [128]. They introduced security aspects to the EED problem as an additional objective and the problem was solved considering tri-objectives. Reference [129] presents an application of the genetic algorithm approach combined with heuristics to force the feasibility of the search region to solve the EED problem. The authors used fuzzy logic to combine the objectives into one and the developed algorithm has the option of fuel switching to assess different alternatives. However, the algorithm seems to generate few dominated solutions when constructing the tradeoff curves. Rughooputh and King incorporated elitism into the traditional NSGA to improve the diversity of non-dominated solutions in the Pareto front of the two conflicting objectives and to reduce the computational complexity [130]. They provided a fuzzy based tool to help the operator select the most desirable operating condition among different non-dominated solutions. They extended their work in reference [131] to capture a Pareto optimal front that accounts for three objectives (fuel cost and two emission types). King *et al.* accounted for the stochastic nature associated with the decision variables and system demands to formulate the EED as a stochastic multi-objective optimization problem [132]. Also, a measure of the system reliability is incorporated as an additional constraint in their formulation. They then used the NSGA approach similar to what was developed earlier in reference [131]. It is important to note that one of the main features of NPGA, NSGA, and SPEA algorithms is their ability to capture a well distributed set of non-dominated solutions in a single run.

4. Evolutionary Programming:

An evolutionary programming based approach with modified solution accerlation techniques was proposed by Wong and Yuryevich to solve the EED problem [133]. They handled the emission as a constraint while minimizing the fuel cost function to produce a single non-dominated solution for each loading condition. Tsay *et al.* proposed an interactive model for optimal operation of cogeneration systems in a petroleum company that consumes different fuels [134]. They developed a full scale model that incorporates various operational constraints on boiler, turbine, power generation, and emission. The EED was formulated as a bi-objective optimization problem with the fuel cost expressed in terms of the cost of different fuel types and total operation cost of boilers while NO_x emission is expressed as a function of each given boiler over a time horizon. The two objectives were combined using the minimum least square error approach and evolutionary programming was employed to minimize the resultant function. In reference [135], the author re-attempted the same problem while accounting for all three emissions in the objective along with the fuel cost.

5. Fuzzy Set Theory:

Srinivasan *et al.* employed fuzzy operators to aggregate four conflicting objectives namely fuel cost, security, emission, and reliability to form the multi-objective problem [136]. Then, an integration of the fuzzy expert system with pattern recognition techniques was utilized to optimize the overall decision making function. The uncertainties of computing the fuel cost and emission coefficients were considered in the problem formulation in reference [137]. The coefficients were represented as fuzzy numbers and the two objectives were combined into one by using a weighted ideal point method. A hybrid approach of evolutionary algorithms and quasi simplex was developed to solve the fuzzy nonlinear programming problem.

6. Differential Evolution:

The authors in reference [138] adapted this newly developed meta-heuristic tool to solve the EED problem. Two different formulations were considered with the first having the fuel cost as a single objective and including emissions as a constraint, while the second approach combined the two objectives by using the weighting method.

4.4 Survey of the Optimal Power Flow

This section offers a general recent review of most of the research work conducted with regard to the OPF. Due to the abundant number of reported OPF articles, only non-classical OPF solution methods are addressed. A detailed review of major classical solution methods to the OPF problem is presented in references [2;3;139]. Reviewed papers are extracted from the IEEE database and categorized based on the solution method as follows:

1. **Genetic Algorithms-Based Approach:**

Gaing and Huang presented a real-coded genetic algorithm for the OPF problem with the objective function being the quadratic fuel cost function [140]. In their formulation, the authors accounted for both discrete and continuous optimization variables and introduced prohibited zones of the generation units as additional constraints. In reference [141], a similar OPF formulation was considered with the inclusion of the non-convex fuel cost function to better model the rippling effects in the I/O curve of the generating units due to the valve admission. The prohibited zones constraints were relieved in this formulation. Zhang *el al.* introduced a transient stability index as an additional inequality constraint, to account for the impacts of different contingencies on the transmission network stability, to their OPF formulation [142]. They employed a binary version of the genetic algorithm to test their proposed approach in the deregulated market of the United Kingdom. An enhanced binary version of the genetic algorithm with advanced and problem-specific operators was developed by Bakirtzis *et al.* to solve the OPF problem [143]. This enhancement improved the convergence rate and the quality of solutions. The proposed approach was tested using the quadratic fuel cost function as an objective of the OPF. Using the same objective function, a comparison of the performance of two metaheuristic methods (namely PSO and enhanced genetic algorithm) and two available commercial grade optimization software packages that employ nonlinear mathematical programming methods (LINDO and GAMS) was made in references [144;145]. In this problem formulation, both the discrete and continuous nature of the optimization variables were accounted for. In the case of the metaheuristic methods, the authors transformed the constrained OPF problem into an unconstrained problem by using the penalty factors approach. The authors have concluded that metaheuristic methods performed well in small test systems and failed to provide feasible solutions for medium-size test systems. Todorovski and Rajicic have proposed a special initialization procedure for the control variables of the OPF problem to generate an initial set of solution vectors with no or few constraint violations [146]. A real-coded genetic algorithm based approach was used to solve the optimization problem and results indicated significant reduction in the computation time. In their proposed solution method, they used a distinct and unconventional set of control variables to optimize the quadratic fuel cost function. They chose the complex voltages at the generator-buses (i.e. both magnitudes and phase angles), reactive power of synchronous condensers, transformer tap settings, and shunt device settings to be the control variables. The unusual usage of the phase angles at the voltage controlled buses as control variables is based on earlier research conducted by the same authors in which they have developed a new innovative way to solve the power flow equations using genetic algorithm [147]. Their proposed approach appears to be faster than the fast decoupled method in solving the power flow equations and it eliminates the concept of predetermined slack bus. Devaraj and Yegnanarayane have used a real-coded genetic algorithm technique to solve the OPF problem to improve system security [148]. They used a severity index, a measure of the severity of the contingency to line overloading condition, as an objective function in their formulation. The control variables selected were the phase angle of the phase-shifting transformer (discrete) and the real power outputs and voltage magnitudes of the generation units (continuous). Proper placement of the phase-shifting transformers was achieved based on sensitivity analysis.

Das and Patvardhan treated the OPF as a multi-objective optimization problem with four different objective functions, i.e. fuel cost and emissions of the generating units, transmission real power losses, and the security margin index [149]. They combined genetic algorithm with simulated annealing to form a hybrid solution tool with enhanced capability of handling both discrete and continuous control variables. The shape of the Pareto front was detected and they determined the best comprising solution of the OPF multi-objective optimization problem. Similarly, Abido proposed a strength Pareto evolutionary algorithm to solve the multi-objective OPF problem [150]. In his formulation, Abido considered two objective functions, namely the fuel cost and the voltage stability indicator. An entire set of Pareto optimal solutions were calculated and the Pareto shape was captured.

Lai and Ma proposed a binary-coded genetic algorithm approach to solve the OPF problem in FACTS [151]. They used a unified power flow controller (UPFC) to regulate the power flow such that the real power losses were minimized. Several contingencies were considered to successfully test the proposed approach. Padhy *et al.* used a different FACTS device, namely a thyristor-controlled series compensation (TCSC), to minimize an objective function that sums the complex power lost in transmission lines (i.e. real and reactive line losses) and the generated reactive power [152]. A hybrid tool of which genetic algorithm was used to locate the optimal placements and settings of TCSC devices and a quasi-Newton algorithm was then employed to solve the OPF problem. Reference [153] presents a genetic algorithm approach that makes use of both UPFC and TCSC devices to maximize the transmission lines capacity. Two similar applications of employing genetic algorithm in solving the OPF problem are presented in references [154;155]. In both cases, a binary-coded genetic algorithm coupled with a power flow algorithm is used to minimize the quadratic fuel cost function with the inclusion of UPFC settings as additional control variables. Chung and Li incorporated settings of the TCSC and thyristor-controlled phase shifter (TCPS) into the OPF problem that minimizes the quadratic fuel cost function [156]. A genetic algorithm was used to determine the optimal settings of the used FACTS devices.

With the deregulation of the electric power industry, new OPF formulations have emerged to represent the new environment in which genetic algorithm versatile capabilities were further employed. Gountis and Bakirtzis have formulated a two level optimization problem to optimize the bidding strategies of electricity producers [157]. They developed a model that takes into account the uncertainty of nodal loading conditions and the market risk factors. The problem was solved by forming a hybrid tool of Monte Carlo simulation and genetic algorithm. Dong and Hill used a risk analysis to optimally schedule the reactive power, a form of ancillary services, in the electricity market [158]. They combined linear programming and genetic algorithm to minimize an objective that represents the future risk of possible scenarios. Reference [159] presents an application of genetic algorithm in calculating the available transfer capability of a power network in a deregulated market.

2. Evolutionary Programming:

Lai and Ma introduced evolutionary programming as a viable tool to minimize the real power losses in power networks by regulating the power flow via optimal UPFC settings [160]. The proposed approach was tested under various contingencies scenarios. Venkatesh *et al.* made use of evolutionary programming to solve the OPF problem while accounting for UPFC in their formulation [161]. They addressed the problem considering two fuzzy objective functions, i.e. minimum of the real power losses and the best voltage profile, while accounting for the nature of control variables used. Ongsakul and Jirapong used evolutionary programming to maximize the total transfer capability between generation and load center areas [162]. The proposed approach optimally adjusts the real power outputs and voltage magnitudes at generation buses such that the total load in the sink area is maximized. They further enhanced their approach to determine the optimal settings and locations of four types of FACTS devices in addition to the other previously considered control variables to optimize the same objective [163]. Reference [164] presents a multi-objective formulation of security constrained OPF problem with the objective functions being the quadratic fuel cost and active power losses. In this application, a hybrid tool of evolutionary programming and SQP was developed in which the former method is used to find good initial solution for the latter method. This hybridization reduced the computation time and outperformed the performance of each individual method. The developed algorithm was tested under different contingency cases on a test system composed of two interconnected areas. Shi *et al.* proposed a hybrid method that combines evolutionary programming and a classical gradient search method to minimize the quadratic fuel cost function [165]. Lo *et al.* developed a parallel evolutionary programming approach to minimize the quadratic fuel cost function [166]. A master-slave set up of 31 computers was used to test their proposed approach on two test systems. They compared their results to those of sequential evolutionary programming and concluded that both approaches were comparable in terms of the solution quality. However, parallel evolutionary programming reduced the execution time by a factor of 10-12 times. The same authors extended their work by incorporating the steepest descent as a local search mechanism for a portion of the population within evolutionary programming to improve the speed of convergence [167]. In addition, three configurations of parallel evolutionary programming, namely master-slave, dual-ring, and 2D-mesh, were implemented to solve the OPF problem. Comparison results reveal that 2D-mesh configuration of parallel evolutionary programming provided a better solution at a faster convergence rate.

Padhy solved the OPF problem using evolutionary programming in order to calculate the wheeling rates of active power at various parts of the transmission network [168]. He used the quadratic fuel cost function to test his approach. Sood *et al.* presented a hybrid method to calculate the wheeling rates of both real and reactive power based on the solution of the OPF [169]. Evolutionary programming was combined with the steepest decent method to minimize different types of fuel cost functions such as continuous quadratic, piecewise quadratic, piecewise linear with prohibited operating zones, piecewise quadratic with prohibited operating zones, and quadratic with a superimposed sine term to account for valve loading effects. A similar hybrid method was presented in reference [170] to optimize the voltage profile with three types of fuel cost functions. In reference [171], a hybrid method of evolutionary programming and the Newton-Raphson method was formed to optimally select the best wheeling option when a privately owned generator is introduced in an existing network. The incremental costs of three options were computed based on the OPF calculations to make the proper judgment about the best wheeling option.

3. Artificial Neural Network:

Reference [172] presented an application of using a modified Hopfield neural network to solve the OPF problem with the objective being the incremental fuel cost. Two types of neuron transfer functions were used to investigate the robustness and accuracy of the proposed approach with regard to the OPF. Nguyen developed a neural network that performs Newton-Raphson based OPF calculations to minimize the real power losses [173]. A key feature of his developed network is the parallel computation, i.e. reduced computation time, which makes use of the sparse nature of the OPF matrices. Dondo and El-Hawary proposed a methodology for real-time electricity spot pricing using neural networks [174]. They were able to express the electricity rate in terms of the solution of the OPF problem. Results of the neural network based solution were comparable to those of MINOS, an optimization software package, in terms of solution accuracy and better in terms of execution time. Luo *et al.* used a faster training algorithm, i.e. Quickprop, to train a neural network to maximize the transfer capability of electric power among different areas [175]. The problem was formulated as an OPF where different contingencies and loading conditions were considered during the training process. The proposed network was heavily tested and its performance was compared to the exact solution of the OPF. The same authors extended their work in reference [176] where they compared their neural network performance when considering two different training algorithms in addition to adding more contingencies and loading profiles. In a different application, Luo *et al.* combined a neural network with a Monte Carlo simulation to present a fast computing method to evaluate power system reliability [177].

The problem was formulated as an OPF problem with the objective being minimizing the sum of the load shedding at each bus.

4. Fuzzy Set Theory:

Abdul-Rahman *et al.* developed a fuzzy linear model to include electromagnetic field effects as additional constraints imposed on the OPF problem [178]. The objective was to reach a compromise solution that minimized the fuzzy incremental fuel cost while satisfying the traditional OPF crisp constraints by redirecting the generated power such that the electromagnetic field fuzzy levels at some critical buses are kept within acceptable limits. In a different formulation, a fuzzy representation was used to model the uncertainty of loading conditions in reference [179]. Different membership functions were used to model different elements of the OPF problem that account for contingencies. Various objective functions, namely fuel cost, static security, and emissions, were aggregated using a fuzzy operator to reach a compromise solution of the conflicting objectives. Ramesh and Li modeled the OPF problem as a multi-objective optimization problem with the conflicting objectives being the pre-contingency operating cost and post-contingency correction time [180]. The two functions were formulated as fuzzy objectives subject to hard constraints and SQP was used to solve the problem. A nonlinear predictor-corrector primal-dual interior point method was used in reference [181] to optimize a multi-objective OPF problem. The authors considered optimizing fuzzy functions that model the total generation cost and the deviation of actual loading conditions from an ideal loading condition. Wu used fuzzy rules to improve the efficiency of a predictor-corrector interior point algorithm for the OPF [182]. The proposed approach was tested on a large power system and an average of 20% improvement in computation time was reported. A fuzzy dynamic programming approach was employed to solve the OPF problem that was modeled with fuzzy objective function and fuzzy loads in reference [183]. Padhy made use of the gradient descent method to solve the traditional OPF in a deregulated power environment with the objective being the quadratic fuel cost [184]. Then, he introduced the so called "fuzzy opinion matrix approach" to critically select the most suitable feasible transaction such that the network congestion is reduced.

5. Others:

Tripathy and Mishra introduced a bacteria foraging algorithm to solve the multi-objective OPF problem that optimizes the real power losses and voltage stability limit simultaneously [185]. The control variables considered were the UPFC optimal placement and location in addition to the existing transformer settings. A dynamic version of the bacteria foraging algorithm was developed by Tang *et al.* to minimize the quadratic fuel cost function [186]. The OPF was solved considering a dynamic loading environment using the traditional control variables. A Tabu search was employed to solve the OPF with non-convex fuel cost functions in reference [187]. The simulated annealing technique was proposed to minimize the convex fuel cost function in solving the OPF in reference [188]. The optimal settings and placements of FACTS devices were included in the OPF formulation considered by Bhasaputra and Ongsakul [189;190]. A hybridization of the Tabu search, simulated annealing, and quadratic programming was formed to minimize the quadratic fuel cost function. Lin *et al.* developed an ordinal optimization theory-based algorithm to solve the discrete OPF [191]. They investigated the validity of the proposed algorithm with the objectives being fuel cost function and real power losses.

4.5 Summary

Section 4.2 presents a summary of PSO applications in power systems. It highlights many applications in which PSO was successfully applied, yet it reveals some additional unexplored areas where it can be further employed like protection, restoration, etc. Also, deregulating all major parts of the electric power industry led to the emergence of new operation philosophies that will reformulate many of the established power system optimization problems. This will justify using the PSO to tackle such problems. Another promising research area with regard to PSO is hybridization. Recently, many power systems researchers attempted to combine the PSO algorithm with other techniques to form hybrid tools. PSO adaptability to be integrated with other deterministic and evolutionary optimization algorithms is expanding. This hybridization extended PSO capabilities and improved its accuracy and computation time. This chapter also emphasizes the need for future mathematical investigations of PSO characteristics and behavior in its search for optimal solution. PSO is still in its infancy and further development and research are needed to enhance its overall performance characteristics. Sections 4.3 and 4.4 present major research conducted in the areas of EED and OPF. Both sections are arranged based on the solution method used so that any future extensions of the published work can be easily identified.

Chapter 5

Economic and Environmental Operational Aspects of Power Systems

5.1 Introduction

Of the different primary energy sources that are used to generate electric power the main ones are thermal, nuclear, hydro, and renewable sources. Thermal power plants that consume fossil-based fuel as a primary energy source are the major contributor to the world-wide electric power production. Figure 5.1 shows the electric power generation by the source type in the USA for the year 2005 based on data provided by the US Energy Information Administration [192].

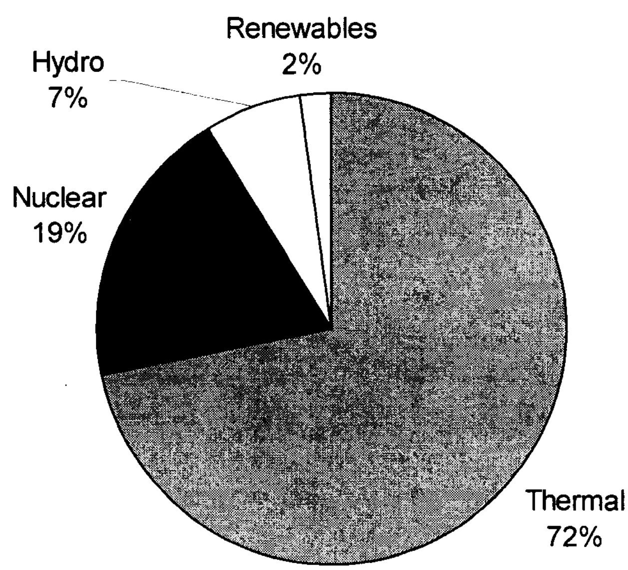

Figure 5.1. US electrical power generation by energy source for 2005.

The heart of each electric power plant is the generator that converts mechanical energy to electrical energy. This conversion takes place in steam turbines by directing the steam produced in the boiler to drive the turbine-generator set. A typical simple set up of a fossil-based power plant is shown in Figure 5.2.

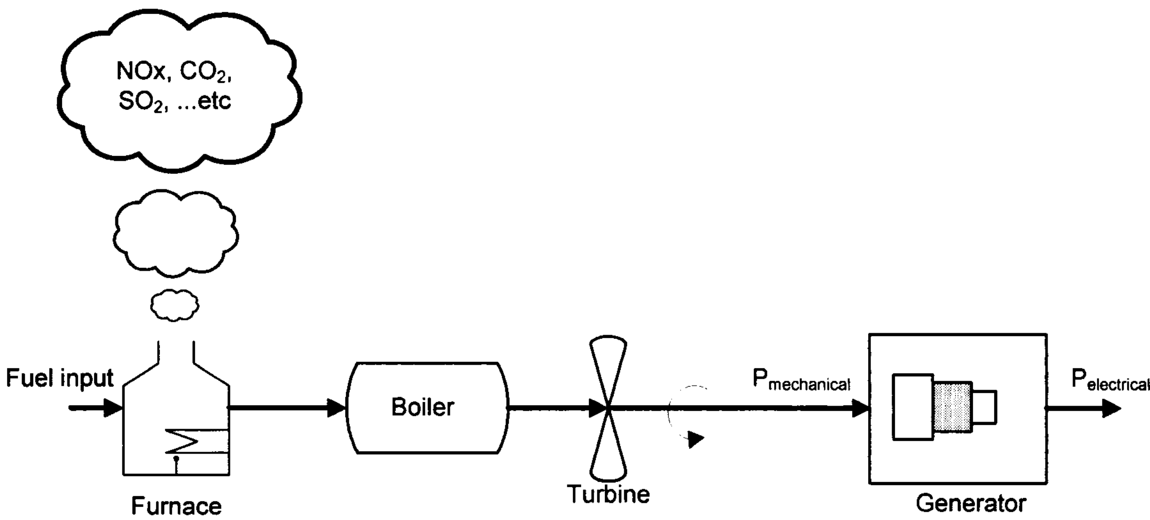

Figure 5.2. Layout of major elements of a thermal power plant.

It is always desirable to operate electric power plants in an optimal manner (i.e. at the lowest possible cost) while meeting certain standards related to quality of service, safety, reliability, and environmental impact. The input-output curve, commonly known as the heat rate curve, of a thermal power plant relates the rate of fuel burnt in Btu/h to the amount of electrical power produced in MW. The shape of this curve is determined based on data collected from field testing of the generating units. It is customary to transform the heat rate curve into its equivalent fuel cost curve that represents the production cost of the electrical power generated. One common way to deal with other costs associated with maintenance and operations is to express them as a fixed percentage of the cost related to total fuel used [193]. Usually, the fuel cost is expressed as a smooth quadratic function as shown in Figure 5.3. Mathematically, it can be represented as follows:

$$F(P) = a + bP + cP^2 \text{ \$/hr} \tag{5.1}$$

where a, b, and c are non-negative constants determined based on curve fitting techniques of the data provided from field testing.

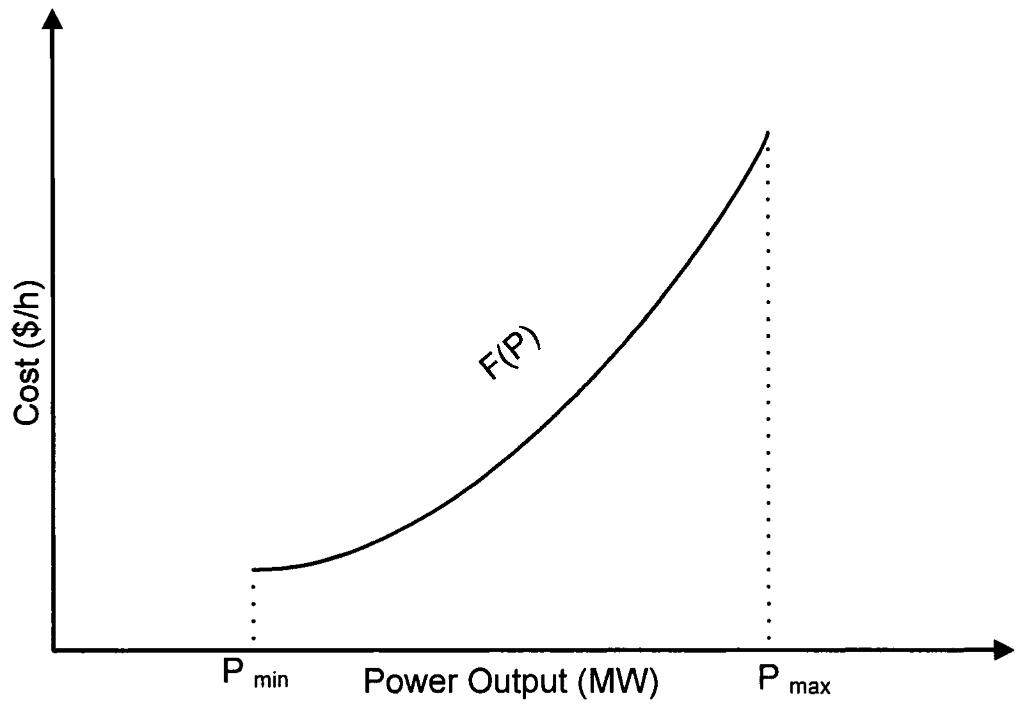

Figure 5.3. Fuel cost curve of a thermal power plant.

When considering N number of power plants, the overall cost function can be modeled as follows:

$$F_T(\mathbf{P}) = \sum_{i=1}^{i=N} (a_i + b_i P_i + c_i P_i^2) \text{ \$/hr} \tag{5.2}$$

where a_i, b_i, and c_i are the cost function coefficients of the i-th generating unit.

5.2 Economic Cost Dispatch

The main objective of Economic Cost Dispatch (ECD) is to allocate the optimal power generation from different units at the lowest cost possible while meeting all system constraints. Note that the terms "economic cost" and "fuel cost" will be used interchangeably. The optimization problem of the ECD can be formulated as follows:

$$Minimize\ F_T(\mathbf{P}) = F_1(P_1) + F_2(P_2) + \cdots\cdots + F_N(P_N) = \sum_{i=1}^{i=N} F_i(P_i)\ \$/\mathrm{hr} \tag{5.3}$$

while satisfying the following two types of constraints:

1. Generating unit capacity limits as inequality constraints

$$P_i \min \leq P_i \leq P_i \max \tag{5.4}$$

2. Generation-demand balance including losses as an equality constraint

$$\sum_{i=1}^{i=N} P_i - P_L - P_D = 0 \tag{5.5}$$

where P_D is the total system real power demand and P_L is the system real power losses. Equation (5.5) states that the total units' generation shall meet system load demand and losses. Various ways were proposed to handle the power losses within the context of the ECD problem with the main ones being:

1. Ignore system losses and supply enough power to meet the demands. Even though this assumption may be computationally acceptable in some power systems with power losses within a few percentage points of what is being generated, it may not always hold since power losses can be a significant portion of the generated power. The amount of power lost is governed by the system topology and operational practices, e.g. power generation far from load centers would result in more losses than generating power near the load, types of conductors used to transfer electricity throughout different segments of the grid…etc.
2. Calculate losses based on the solution of the power flow equations. This gives accurate representation of the actual system losses. However, it adds an extra burden on the computation aspects of the ECD and it is usually considered when performing OPF calculations.
3. Use approximate means to calculate the system power losses. This method provides a compromise between modeling accuracy and computational

complexity and will be used to solve the ECD problem. The most common approach to estimate power losses is by using the approximate loss function [194]:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N}(P_i B_{ij} P_j) \tag{5.6}$$

It is quite common to estimate the real power losses in power networks by computing the *B*-coefficients loss matrix shown in Equation (5.6). It should be noted here that there are two main assumptions made behind this formulation:

1. The network losses are exclusively dependent on the active power generation levels (i.e. reactive power injection effects are neglected).
2. The *B*-coefficients loss matrix depends on the operating state of the power system. If there are no significant changes to the operating state of the power system, the *B*-coefficients loss matrix can be assumed to be constant.

Historically, the ECD was solved by dispatching the generating units in a sequence order based on their efficiency. In this approach, the most efficient unit is dispatched first to its maximum rating then the second most efficient unit is loaded to its maximum loading capability, …etc. This was followed by introducing the equal incremental production cost concept (i.e. partial derivative of fuel cost with respect to the power or $\partial F_i / \partial P$) that minimizes the overall cost by requiring that the incremental production cost of all committed units be equal. Modeling simplifications like ignoring the power network losses is one of the shortcomings among others of the early solution approaches. New solution methods were utilized to cope with various constraints with regard to the ECD problem as a result of the rapid progress in optimization techniques development. Some of the optimization techniques used to solve the ECD problem are:

1. Linear programming [195-198].
2. Quadratic programming [199-201].
3. SQP [202;203].

In depth coverage of various techniques used to solve the ECD problem can be found in reference [204].

Recently, the ECD problem has been attracting more attention due to the competitive market environment that resulted from power system deregulation and higher fuel costs. Also, the development of modern optimization techniques that relieve some of the assumptions that previously had to be accounted for when considering derivative-based solution methods encouraged many researchers to revisit the ECD problem. Recent work in this area focuses on finding a global solution and more precise modeling of this problem.

5.3 Emission Dispatch

Fossil fuel based power generators are blamed for being a major contributor to air pollution. There are various harmful emissions produced in power plants but their primary gaseous pollutants are carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x). Carbon dioxide and sulfur dioxide emissions are highly dependent on the type of fuel used while nitrogen oxide emissions mainly depend on the combustion process used in power generation. Coal, heavy oil, and natural gas are the main fossil-based fuels used to generate electricity with each having different chemical composites. Generally, coal, natural gas, and heavy oil has a carbon content of about 65%, 70%, and 87% respectively, while the sulfur content is quite considerable in heavy oil and coal and it is almost negligible in natural gas [205]. Several hazardous conditions can be encountered when these chemicals interact with the outside environment. Some of these effects are eyes irritation, respiratory diseases, vegetation damage, acid rain, and of course for their long term contribution to global warming. In the past few decades, environmental awareness led to the imposition of rigid environmental policies on power utilities to regulate their emissions. The emissions of air pollutants came under US federal regulations in 1963 when the Clean Air Act law was enacted and it was followed by amendments to that law in 1990 [206]. Globally, most industrial countries, except the two major world polluting countries: USA and China, signed the Kyoto Protocol in 1997 to reduce the greenhouse gas emissions to an average of 5.2% in the period of 2008-2010 to their levels in 1990. It is estimated that the fossil power plants are responsible for emitting 36% of the total CO_2 emissions produced as a result of man-made activities [207]. Subsequently, power utilities had to restructure their operations and planning practices to meet the new environmental laws. Several options were proposed to reduce unit emissions like [208]:

1. Installing post-combustion cleaning equipment to treat the gases generated as a result of the combustion process.
2. Improving the furnace design and technology used to lower the formation of harmful products due to the combustion process.
3. Chemical treatment during the combustion process.
4. Changing fuels in favor of a different fuel type with fewer pollutants.
5. Dispatching with emission considerations.

The latter option is preferred for economic reasons since no capital cost is needed and it is immediately available for short term operation.

Emission Dispatch (ED) is analogous to ECD with the objective of minimizing emissions instead of cost. Typically, emissions are modeled as a function of the generating units' real power output. Many models were proposed to represent the emission function of thermal generating units but the most known models are presented in [8;209;210]. Early work conducted by Gent and Lamont suggested a combination of linear and exponential terms as follows:

$$E(P) = \alpha + \beta P + \zeta e^{\lambda P} \text{ ton/hr} \tag{5.7}$$

More recent work models the emission function as second order polynomial while others model it as quadratic function combined with exponential terms as follows:

$$E(P) = \alpha + \beta P + \gamma P^2 \text{ ton/hr} \tag{5.8}$$

$$E(P) = \alpha + \beta P + \gamma P^2 + \zeta e^{\lambda P} \text{ ton/hr} \tag{5.9}$$

where α, β, γ, ζ, and λ are the emission function coefficients of a given generating unit. When considering N power plants, the overall emission function can be represented as follows:

$$E_T(\mathbf{P}) = E_1(P_1) + E_2(P_2) + \cdots\cdots + E_N(P_N) \text{ ton/hr} \tag{5.10}$$

The goal of the ED optimization problem is to minimize the overall emission of all committed generating units.

$$Minimize\ \ E_T(\mathbf{P}) = E_1(P_1) + E_2(P_2) + \cdots\cdots + E_N(P_N) = \sum_{i=1}^{i=N} E_i(P_i) \text{ ton/hr} \tag{5.11}$$

subject to the following constraints:

1. Generating unit capacity limits as inequality constraints

$$P_i \min \le P_i \le P_i \max \tag{5.12}$$

2. Generation-demand balance including losses as an equality constraint

$$\sum_{i=1}^{i=N} P_i - P_L - P_D = 0 \tag{5.13}$$

Due to the intrinsic distinctions among various power plants as a result of differences in fuel types used, types of generating units, and the combustion processes, researchers sometimes model the total emissions of carbon dioxide, sulfur dioxide, and nitrogen oxides as a single emission function [7;8;127] while others model it with three different emission functions [105;211]. Both formulations will be investigated and analyzed in this chapter to test and validate the proposed solution technique.

The outcome of a single objective optimization is usually a single optimal solution. On the contrary, in multi-objective optimization there is no single optimal solution to any problem unless an exact preference or "weight" of all objectives is known. This gives rise to finding a set of compromise solutions known as Pareto optimal solutions. When optimizing all objectives simultaneously, Pareto optimal solutions show the tradeoffs among conflicting objective functions.

5.4 Emission-Economic Dispatch Problem Formulation

The EED problem is mainly a mixture of two types of objective functions, ECD and ED subject to equality and inequality constraints stated earlier. The EED problem is formulated as a multi-objective optimization problem with conflicting and incommensurable objectives, i.e. there is no single solution that optimizes all objectives concurrently. Thus, ECD and ED functions both have to be considered simultaneously to find the optimal dispatch. It is formulated mathematically as follows:

$$Minimize\ \mathrm{z} = [F_T(\mathbf{P}), E_T(\mathbf{P})] \tag{5.14}$$

subject to

$$g(P) = 0 \tag{5.15}$$

$$h(P) \leq 0 \tag{5.16}$$

where Equation (5.15) is the equality constraint for the generation-demand balance while Equation (5.16) represents the set of inequality constraints that model the lower and upper bounds imposed on the generating units. There is a trade-off relationship between ECD and the ED multi-objective optimization and the goal here is to be able to construct the shape of Pareto optimal set.

5.5 Solution Methodology

One common way to handle optimization problems with conflicting objectives is to combine them into a single scalar function. The following two aggregation methods will be investigated to capture the Pareto front for the EED problem:

1. Weighting method: In this approach the two functions are combined into one as follows:

$$Minimize\ \mathrm{z} = \eta_1 F_T(\mathbf{P}) + \eta_2 h E_T(\mathbf{P}) \tag{5.17}$$

where η_i is the assigned weight that reflects the decision maker's preference in each objective. The total weights are related by $\sum_{i=1}^{K} \eta_i = 1$ for k number of objectives. The symbol h is a scalar factor used to scale different objectives. Note that when $\eta_1 = 1$, the overall problem is reduced to the traditional ECD problem and, likewise, when $\eta_1 = 0$ the problem becomes a pure ED problem. It is important to realize that these two cases represent the two extremes of the Pareto front as shown in Figure 5.4. Any intermediate point along Pareto front corresponds to an optimal solution based on the assigned weights.

2. Varying price penalty factor: In this method the conflicting objectives are combined by assigning a penalty factor to one of the objectives as follows:

$$Minimize\ z = F_T(\mathbf{P}) + D \bullet E_T(\mathbf{P}) \tag{5.18}$$

The Pareto optimal set of the resultant objective can be captured by varying the value of the penalty factor D. Note that if $D = \infty$ the problem becomes one of pure emission dispatch and if $D = 0$ the problem is changed to economic dispatch.

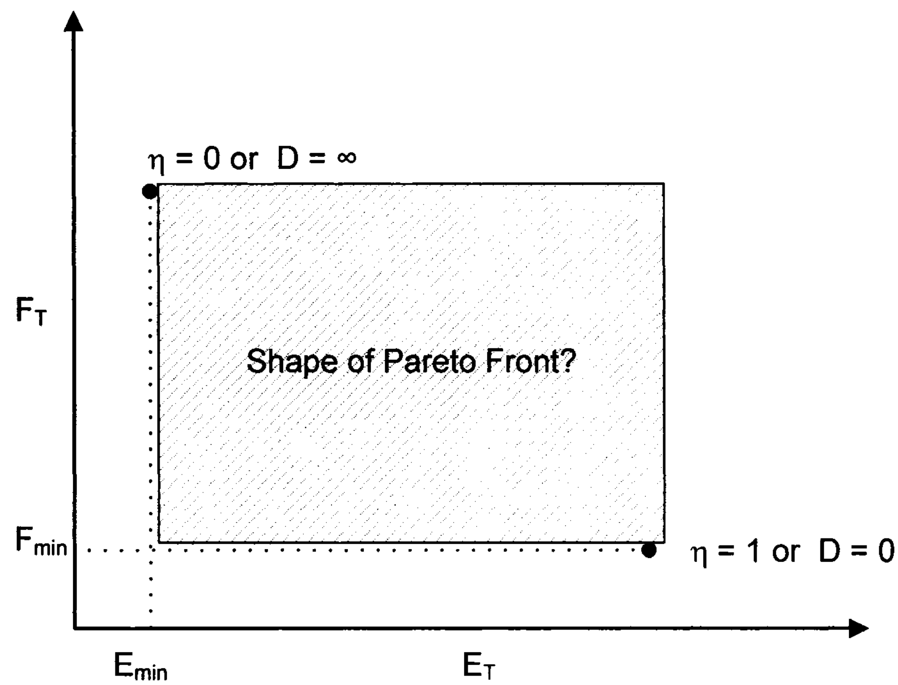

Figure 5.4. The two extreme points of the Pareto front.

5.5.1 Proposed PSO Approach

A PSO program was developed within the Matlab® computing environment to investigate its performance with regard to the EED problem. An extensive number of experiments were conducted to tune the proposed PSO algorithm to effectively solve the problem. In each experiment, the PSO algorithm is executed 50 times once one of its parameter has changed. Proper PSO settings are determined based on consistency in reaching the optimal solution. The average, best, and worst performance of each experiment are then calculated. Figures 5.5-5.7 show the results of PSO parameters tuning. The stopping criterion for all experiments is set to a maximum of 800 iterations. The inertia weight is kept constant throughout all experiments with a range of 0.04-0.09. These values are based on previously published works and are found to be suitable for the EED problem [27]. The standard deviation of each experiment is shown in Table 5.1. The optimal PSO parameters are selected as follows:

- Number of Particles = 20.
- $V_{max} = 2.0$.
- Acceleration Constants = 1.25.

Table 5.1. A Study of Tuning PSO Parameters for the EED

Parameter		Ave	Min	Max	St. Dev.	Other HPSO Parameters
C_1,C_2	0.10	608.410	600.380	622.279	4.454	No. of Particle = 10 Max. Velocity = 1 Max. Iterations = 800
	0.25	607.685	602.127	630.414	5.156	
	0.50	605.691	601.257	619.525	3.671	
	0.75	606.524	600.443	622.174	5.118	
	1.00	605.179	600.540	623.450	3.986	
	1.25	**600.818**	**600.112**	**608.961**	**1.835**	
	1.50	601.402	600.112	614.796	2.831	
	1.75	602.184	600.111	610.412	3.240	
	2.00	603.944	600.113	624.480	6.088	
	2.50	601.481	600.112	613.539	3.071	
Number of Particles	5	606.852	600.121	628.848	6.059	C1 = C2 = 1.25 Max. Velocity = 1 Max. Iterations = 800
	10	600.818	600.112	608.961	1.835	
	20	**600.521**	**600.111**	**603.870**	**1.021**	
	30	600.153	600.111	601.405	0.198	
Maximum Velocity	0.01	600.797	600.111	604.414	1.091	C1 = C2 = 1.25 No. of Particle = 20 Max. Iterations = 800
	0.1	600.636	600.111	604.890	1.045	
	0.25	600.481	600.111	604.638	0.958	
	0.5	600.546	600.111	603.999	0.773	
	1	600.521	600.111	603.870	1.021	
	2	**600.196**	**600.111**	**601.338**	**0.275**	
	3	600.8302	600.1114	604.4582	1.121033	

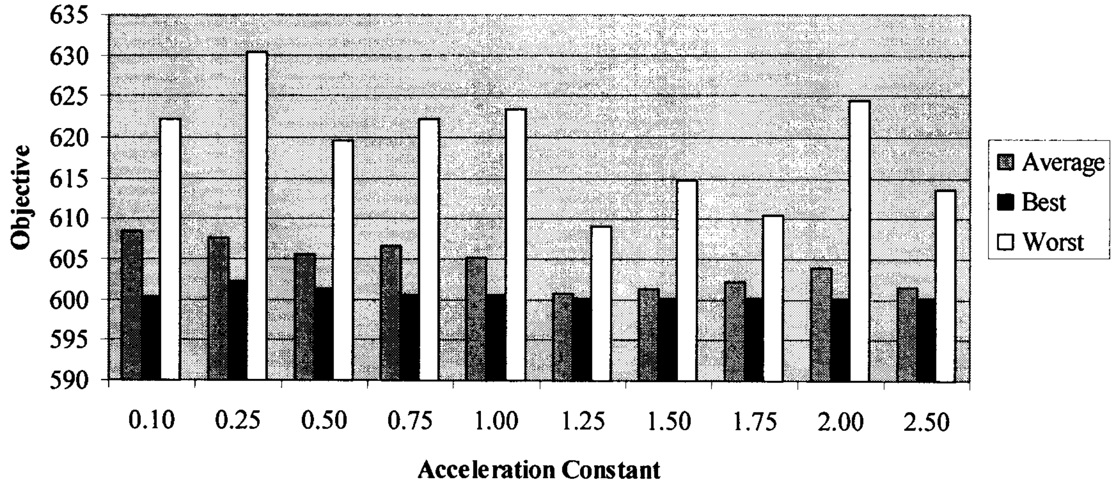

Figure 5.5. Impact of the acceleration constants on the convergence characteristic.

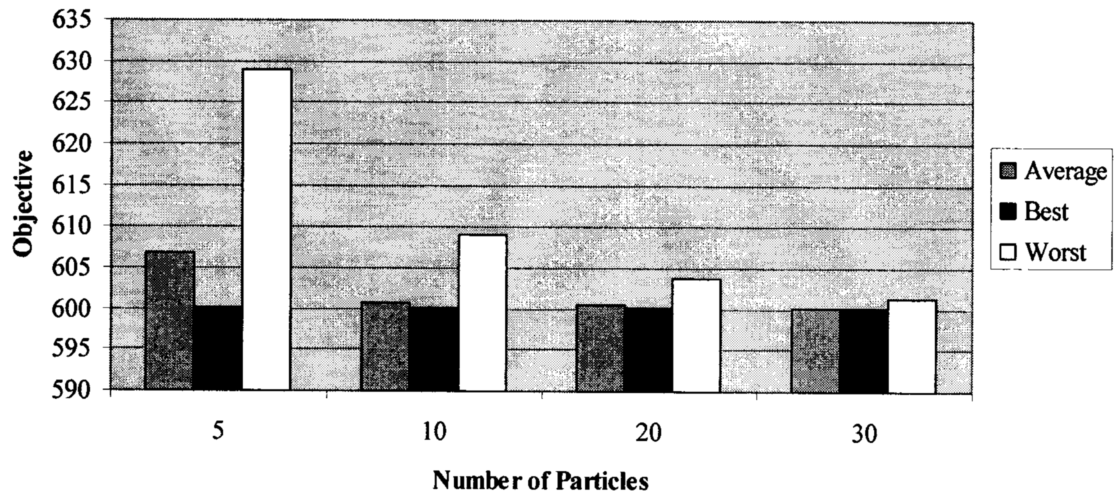

Figure 5.6. Impact of the swarm size on the convergence characteristic.

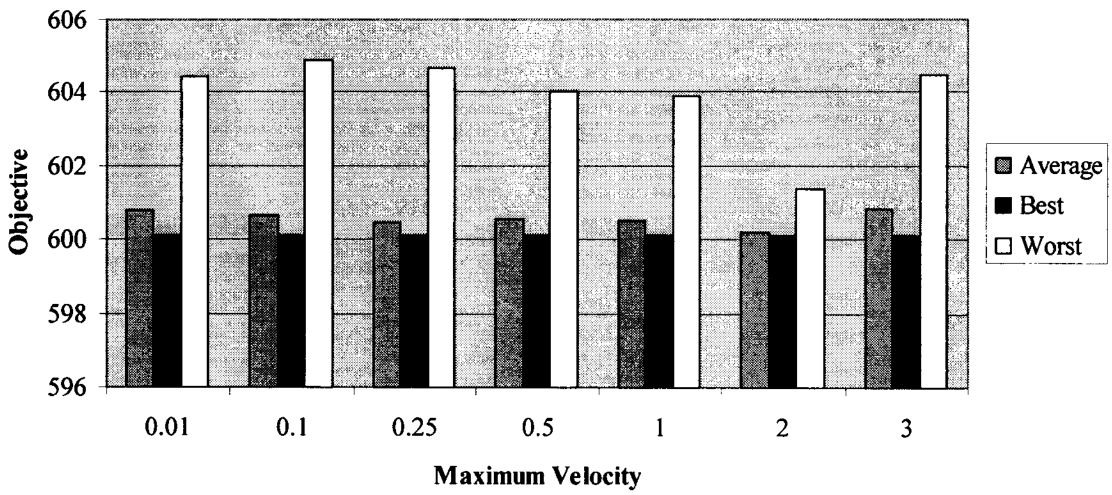

Figure 5.7. Impact of the maximum velocity on the convergence characteristic.

The system constraints increase the difficulty level in developing solution techniques to most optimization problems since the anticipated optimal solution has to satisfy them. In this regard, a special treatment of the EED constraints is presented next.

5.5.2 EED Constraints Handling Mechanism

The formulated optimization problem has both equality and inequality constraints. The equality constraints in particular represent a challenge to most stochastic optimization algorithms since they often hard to satisfy throughout the optimization process. In the context of PSO, constraints are handled as follows:

A. Equality Constraints:

A novel mechanism is proposed in this thesis to handle this type of constraints for the EED problem. At each iteration, the equality constraint shown in Equation (5.13) is satisfied by following the simple yet effective procedure:

1. Ignore network losses at first and randomly generate each particle vector, which represents a unit's power levels, within their bounds except for the last element in that vector as follows:

$$X_i = [x_1, x_2, ..., x_{N-1}] \tag{5.19}$$

2. Calculate the last element for each particle, i.e. the last unit's power level according to the following equation:

$$x_N = P_D - [x_1 + x_2 + ... + x_{N-1}] \tag{5.20}$$

3. Check for the feasibility of the last element. If a violation has occurred go to step 1, otherwise go to the next step.
4. If system losses are not considered, stop this procedure, otherwise go to step 5.
5. Calculate the network losses in accordance with the approximate loss function.
6. Incorporate losses into power generation by adjusting the last unit's power level as follows:

$$x_N = P_D + P_L - [x_1 + x_2 + ... + x_{N-1}] \tag{5.21}$$

7. Re-calculate losses and re-adjust generation.

B. Inequality Constraints:

The particle's position (i.e. power level) is checked after each iteration to ensure its compliance with bounds. If any particle flies outside its bounds, its current position will be restored to its previous best position (*pbest*). This strategy permits only feasible solutions to exist among the population, thus it eliminates the need to use penalty functions. A more elaborate explanation of the impact of this inequality constraint treatment is provided in the next chapter.

This proposed constraint handling mechanism introduces a new approach for the PSO population initialization process. In a typical PSO implementation and in most evolutionary computation methods, the entire population is initialized at random. If this approach is incorporated in the EED problem, the randomly initialized population most likely will not satisfy the equality constraint. This type of constraint represents a major difficulty for most metaheuristic methods. However, the proposed procedure enforces the last element of each particle position vector deterministically to satisfy the equality constraint. Thus it blends both randomness and deterministic natures in initializing the candidates for the optimal solution.

5.6 Simulation and Results

Various testing cases are used to examine and validate the applicability of PSO to solve the EED multi-objective optimization problem. In the study cases under consideration, special attention was given to include different aspects of the EED problem modeling. The main differences are the type of model used for the emission function, the number of objectives, system loss considerations, and aggregation methods. The following cases are used to validate the proposed PSO approach:

A. **Case study 1:** Bi-objective optimization using varying penalty factor method:

The PSO technique was tested on the IEEE 30-bus system with 6 generators and 41 interconnected transmission lines. The system total demand is 283.4 MW which is based on the standard loading condition of this test system [212]. Fuel cost and total emission function coefficients along with each generator's capacity limits are given in appendix A [8]. The emission function considered in this formulation is a quadratic function with exponential term as in Equation (5.9) that represents all types of gaseous pollutants for the first two cases. The system is tested using the following cases:

Case 1: Ignoring system losses, fuel cost and emission functions were minimized individually using PSO, see Table 5.2. Then, losses were considered and both functions were minimized individually, results obtained are shown in Table 5.3. The convergence characteristic of PSO is shown in Figure 5.8 when losses were ignored. When losses were included in the problem, similar convergence characteristics were obtained as shown in Figure 5.9. In both figures, generation represents iterations with improved objective function value. The optimal solutions found in this case show the two ends of the Pareto optimal set.

The results were compared with those for previous studies done in reference [8] in which Evolutionary Algorithms (EA) were used and also against results obtained using LINGO software. LINGO is a commercial-grade optimization tool with built-in global optimization capabilities. Comparison between results is shown in Table 5.4. When network losses were ignored, PSO generated comparable results to LINGO and it generated slightly better results than EA. However, PSO gave improved results compared to EA and LINGO when system losses were included in the problem formulation.

Table 5.2. Best Solutions (Lossless)

Cost Dispatch		Emission Dispatch	
Pg (p.u.)	C(Pg)	Pg (p.u.)	E(Pg)
0.109922	33.192614	0.402285	0.029701
0.299959	65.790910	0.458427	0.011862
0.526262	125.805272	0.540935	0.028520
1.014833	173.276485	0.383863	0.048923
0.522898	125.058537	0.538283	0.028522
0.360126	76.987960	0.510206	0.046677
Total cost ($/hr)	**600.111778**		637.966153
Total emission (ton/hr)	0.222037		**0.194204**

Table 5.3. Best Solutions (With Losses)

Cost Dispatch		Emission Dispatch	
Pg (p.u.)	C(Pg)	Pg (p.u.)	E(Pg)
0.080492	26.746238	0.414015	0.029693
0.303937	66.675909	0.464760	0.011858
0.586878	139.415016	0.547697	0.028517
0.992925	168.446490	0.392175	0.048918
0.533032	127.310654	0.549413	0.028517
0.360029	76.966470	0.518387	0.046673
Total cost ($/hr)	**605.560777**		650.207276
Total emission (ton/hr)	0.221868		**0.194175**

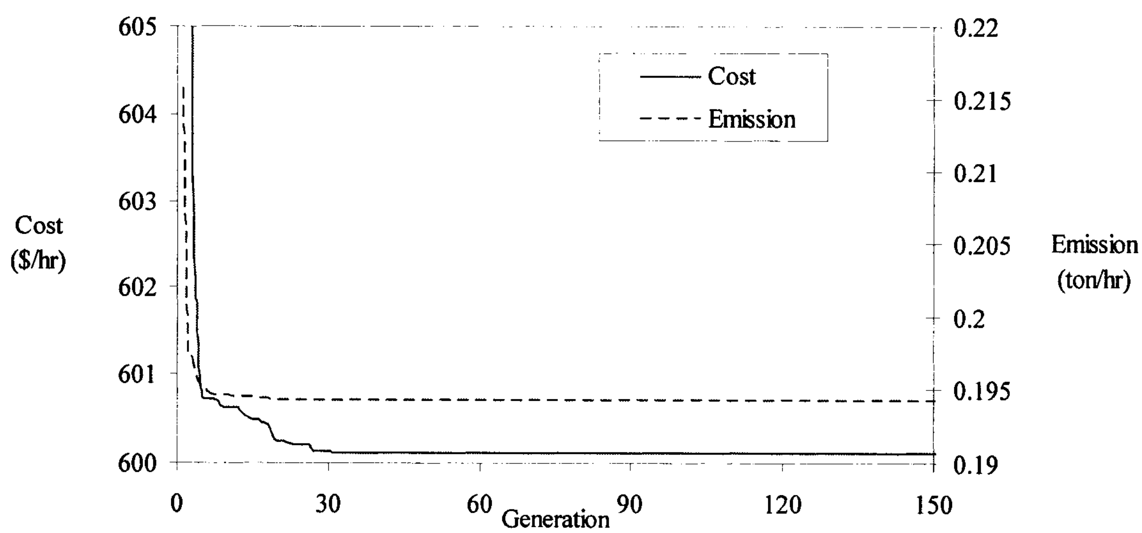

Figure 5.8. Convergence characteristics of minimizing fuel cost and emission functions when losses are ignored, Case 1.

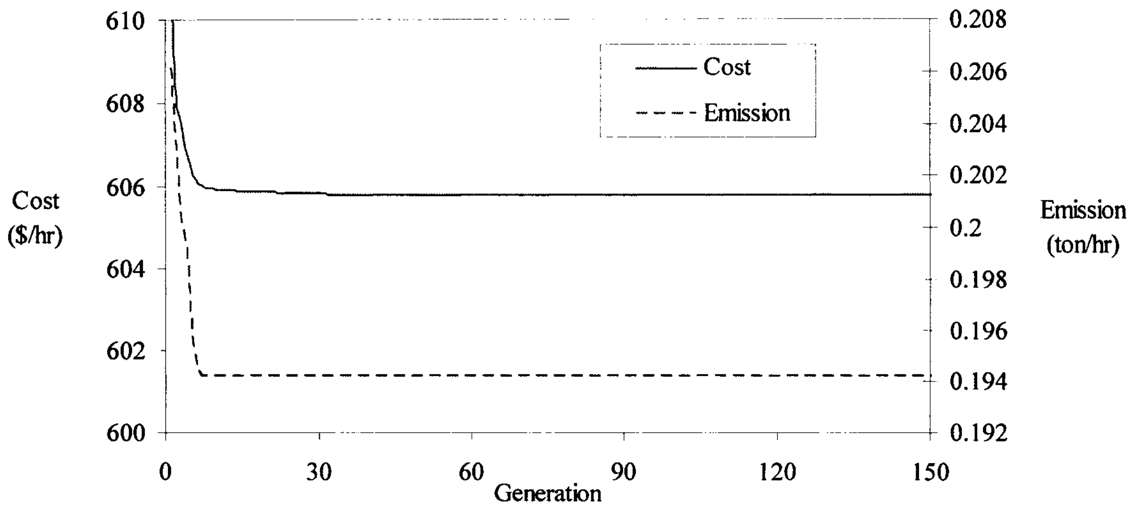

Figure 5.9. Convergence characteristics of minimizing fuel cost and emission functions when losses are considered, Case 1.

Table 5.4. Comparison among PSO, EA, and LINGO

	Considering Fuel Cost Only		Considering Emission only		
	Cost	Emission	Cost	Emission	
EA	600.11	0.2221	638.26	0.1942	Lossless
PSO	**600.11178**	0.22204	637.96615	**0.194204**	
LINGO	600.11143	0.22214	638.27351	0.194203	
EA	607.78	0.2199	645.22	0.1942	With Losses
PSO	**605.56078**	0.22187	650.20728	**0.194175**	
LINGO	605.65822	0.22212	650.34745	0.194175	

Case 2: The multi-objective optimization problem was solved using PSO by means of assigning a price penalty factor to the emission function. This method makes it possible to combine the two objective functions into a single objective. The new combined objective optimization problem is formulated as follows:

$$z = F_T(\mathbf{P}) + D \bullet E_T(\mathbf{P}) \tag{5.22}$$

Different researchers derived formulae to calculate the proper price penalty factor for a given demand [120]. This approach will find a single solution based on the calculated value of D. However, D is varied in the proposed algorithm to generate a trade-off curve between the two conflicting objective functions. Note that when $D = 0$, the combined problem reduces to the conventional fuel cost dispatch problem. Likewise, the problem becomes a pure emission dispatch when $D = \infty$. Figure 5.10 shows the trade-off curve when system losses are ignored, while Figure 5.11 shows the same curve when losses are considered.

The results obtained for Case 2 were compared to previous studies reported in reference [8]. The same system was used to test various techniques reported in the literature, like the Multi-objective Stochastic Search Technique (MOSST), Linear Programming (LP), and EA. Tables 5.5(a) and 5.5(b) show a comparison between results obtained using the aforementioned techniques when network losses were neglected. Results obtained using PSO were compared to those of EA when system losses are considered and tabulated in Table 5.6. It is clear that PSO did slightly better than EA in this case as well.

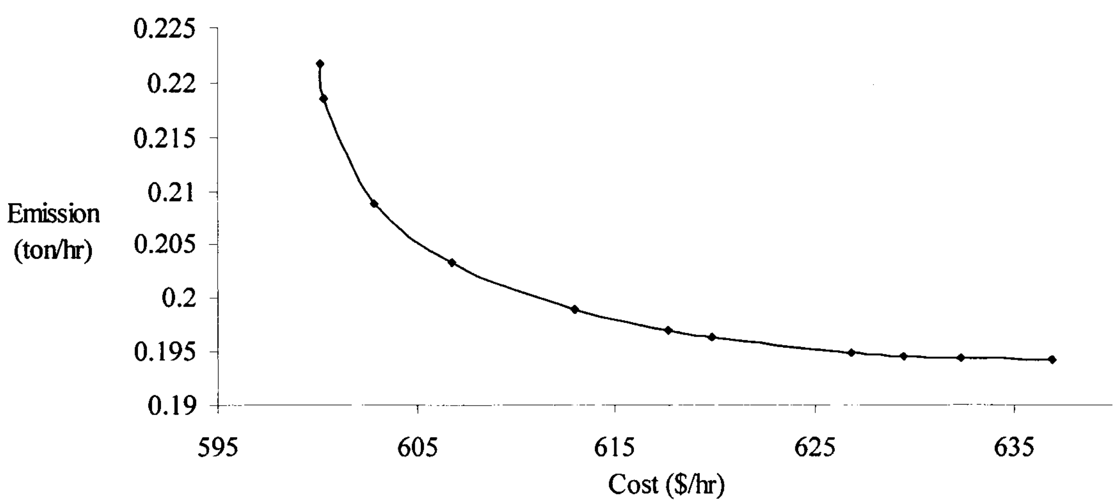

Figure 5.10. The trade-off curve between emission and cost when losses are ignored, Case 2.

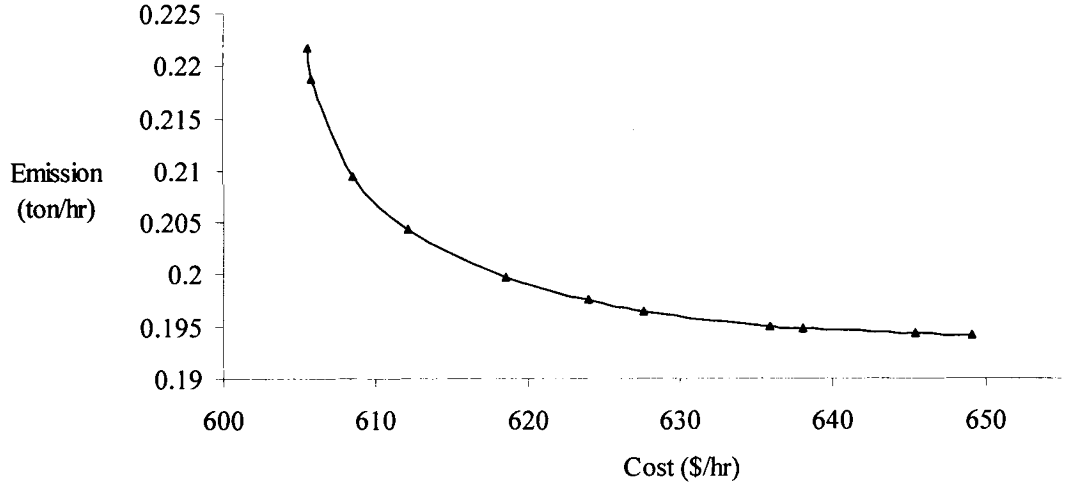

Figure 5.11. The trade-off curve between emission and cost when losses are included, Case 2.

Table 5.5(a). Comparison Between Different Techniques When Losses Are Ignored (Cost)

	Best Cost			
Pg No.	MOSST	LP	EA	PSO
1	0.1125	0.15000	0.06490	0.10898
2	0.3020	0.30000	0.05638	0.29848
3	0.5311	0.55000	0.04586	0.52597
4	1.0208	1.05000	0.03380	1.01489
5	0.5311	0.46000	0.04586	0.52591
6	0.3625	0.35000	0.05151	0.35977
Cost ($/hr)	605.89	606.31	600.15	**600.112**
Emission (ton/hr)	0.2222	0.2233	0.2215	0.2221

Table 5.5(b). Comparison Between Different Techniques When Losses Are Ignored (Emission)

	Best Emission			
Pg No.	MOSST	LP	EA	PSO
1	0.4095	0.4000	0.4116	0.4055
2	0.4626	0.4500	0.4532	0.4499
3	0.5426	0.5500	0.5329	0.5431
4	0.3884	0.4000	0.3832	0.3875
5	0.5427	0.5500	0.5383	0.5385
6	0.5142	0.5000	0.5148	0.5095
Cost ($/hr)	644.11	639.60	638.51	637.54
Emission (ton/hr)	0.1942	0.1942	0.1942	**0.1942**

Table 5.6. Comparison Between EA and PSO When Losses Are Considered

	Best Cost		Best Emission	
Pg No.	EA	PSO	EA	PSO
1	0.1086	0.08160	0.4043	0.4108
2	0.3056	0.30396	0.4525	0.4668
3	0.5818	0.58990	0.5525	0.5484
4	0.9846	0.99763	0.4079	0.3911
5	0.5288	0.52464	0.5468	0.5515
6	0.5384	0.35959	0.5005	0.5173
Cost ($/hr)	607.807	**605.562**	642.603	650.044
Emission (ton/hr)	0.22015	0.2221	0.19422	**0.19418**

B. **Case study 2:** Bi-objective optimization using weights method:

The proposed technique was tested on IEEE 14-bus system with 5 generators and a total demand of 270 MW. The characteristics of the generating units are listed in Appendix A [213]. Note that the exponential term in the total emission model given in Equation (5.9) was eliminated in this case, i.e. a quadratic function is used to model the emission function. Since the goal of this chapter is to test and compare the PSO technique with regard to the EED problem, modeling precision and validity will not be addressed nor discussed here. The multi-objective optimization problem of this system is converted to a single objective problem using the weighting method as follows:

$$z = \eta F_T(\mathbf{P}) + (1-\eta) h E_T(\mathbf{P}) \tag{5.23}$$

In Equation (5.23), h is assigned a value of 0.25 and losses were included. This weight has a range of $[0,1]$. When $\eta = 1$, z in Equation (5.23) transforms to optimizing the fuel cost function only. Similarly, if $\eta = 0$, the problem is reduced to optimizing the emission function exclusively. The Pareto optimal solution set is obtained in this case by changing the weight of each function as shown in Table 5.7. The shape of the Pareto optimal solution set is constructed in Figure 5.12 by obtaining a set of compromising solutions. The same system was optimized using the Adaptive Hopfield Neural Network (AHNN) and LINGO software. Comparison among PSO, AHNN, and LINGO is listed in Table 5.8. PSO generated slightly better results at different weight factors.

Table 5.7. Pareto Solutions at Different Weight Factors

η	P1	P2	P3	P4	P5	F(P)	E(P)
1	100	50.3837	32.0230	25	66.5037	3290.6027	1133.7379
0.9	100	49.6701	32.4308	25	66.7918	3290.6064	1133.4640
0.8	100	48.8945	32.8826	25	67.0965	3290.6188	1133.1850
0.7	100	48.0488	33.3875	25	67.4171	3290.6425	1132.9027
0.6	100	47.1229	33.9571	25	67.7516	3290.6807	1132.6199
0.5	100	46.1051	34.6084	25	68.0949	3290.7382	1132.3407
0.4	100	44.9813	35.3659	25	68.4362	3290.8211	1132.0709
0.3	100	43.7349	36.2687	25	68.7530	3290.9389	1131.8190
0.2	100	42.3464	37.3850	25	68.9963	3291.1067	1131.5975
0.1	100	40.7948	38.8513	25	69.0511	3291.3530	1131.4269
0	100	39.0638	41.0029	25	68.5994	3291.7506	1131.3499

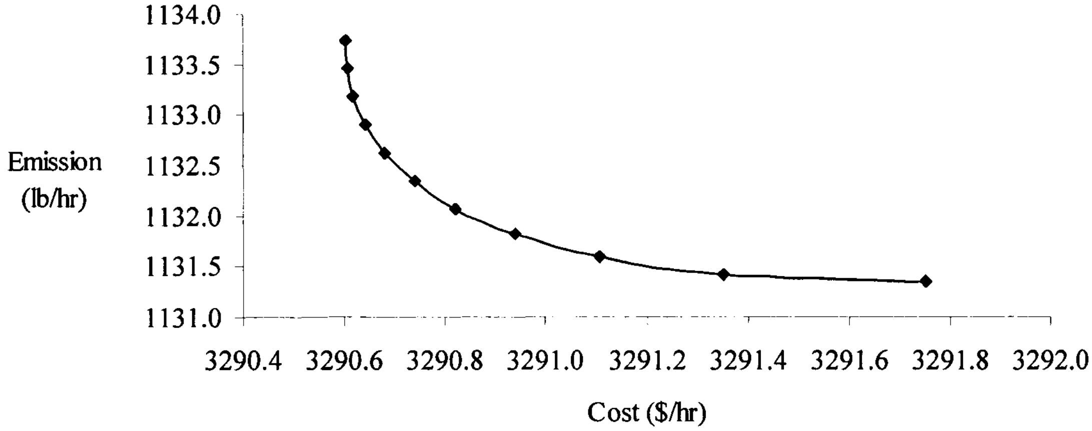

Figure 5.12. Pareto solution shape for 14-bus system.

Table 5.8. Comparison Among PSO, AHNN, and LINGO

η	Method	F(P)	E(P)
1	PSO	**3290.6027**	**1133.7379**
	AHNN	4556.3500	1217.2700
	LINGO	3319.2181	1184.4723
0.9	PSO	**3290.6064**	**1133.4640**
	AHNN	4584.5000	1198.3400
	LINGO	3319.2226	1183.6811
0.8	PSO	**3290.6188**	**1133.1850**
	AHNN	4585.3500	1197.8200
	LINGO	3319.2226	1183.6811

C. **Case Study 3:** Different Loading Conditions:

The test system for case 1 is used to study the impact of loading conditions on the shape of the Pareto front and to ensure the steady performance of the proposed approach. The weighting method is used to aggregate the two objectives under three different loading conditions and ignoring losses in this case. The total system demand is increased by multiples of 20% of the base load, i.e. P_{D1} = 340.08 MW, P_{D2} = 396.76 MW, and P_{D3} =

453.44 MW. Table 5.9 shows the results obtained from the first loading condition. A careful look at the results reveals that the generating units 1, 2, and 6 are very efficient in terms of their emissions but poor in their fuel consumption. Unit 4 is the most efficient one among all the units in terms of economics but it is the worst in terms of its harmful effects toward the environment. Units 3 and 5 maintain somewhat of a balancing performance in terms of emission and economic dispatching. The shape of Pareto fronts for all three loading conditions are shown in Figure 5.13. It appears that the Pareto shape is not affected by the loading condition as it preserves the same characteristics in all three cases. Also, the proposed approach seems to be performing steadily in capturing the shape of the trade-off curves.

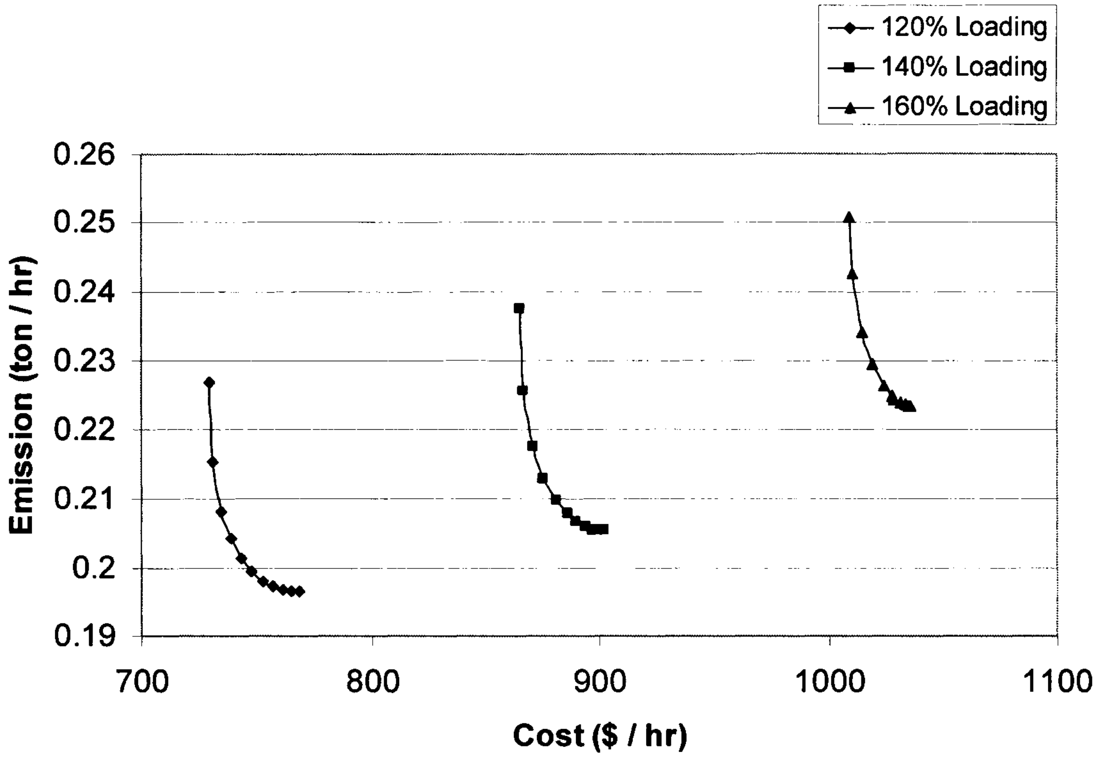

Figure 5.13. Pareto fronts for all three loading conditions.

Table 5.9 Results for the first Loading Condition in Case 3

Weight	P_1	P_2	P_3	P_4	P_5	P_6	Cost ($/hr)	Emission (ton/hr)
1	0.16833	0.34862	0.67196	1.11618	0.67618	0.41954	729.29150	0.22675
0.9	0.23042	0.38141	0.67044	0.99059	0.67525	0.45270	730.83538	0.21555
0.8	0.28742	0.40943	0.67185	0.88523	0.66703	0.47984	734.66780	0.20816
0.7	0.32023	0.43251	0.66551	0.81186	0.66712	0.50357	738.64339	0.20417
0.6	0.35373	0.45533	0.66031	0.74737	0.66177	0.52228	743.24214	0.20129
0.5	0.37972	0.47292	0.65877	0.69518	0.65388	0.54033	747.63726	0.19946
0.4	0.41057	0.48555	0.65335	0.64453	0.65211	0.55468	752.51088	0.19811
0.3	0.43071	0.50187	0.64813	0.60163	0.65220	0.56627	756.96024	0.19732
0.2	0.44815	0.51623	0.65160	0.56367	0.64615	0.57500	761.14894	0.19686
0.1	0.46892	0.51840	0.64511	0.53319	0.64786	0.58731	764.92025	0.19664
0	0.48300	0.53510	0.64174	0.50442	0.64244	0.59410	768.80771	0.19656

D. **Case study 4:** Quad-Objective optimization using the weights method:

The PSO technique was tested on the 30-bus standard test system with six generating units and a total demand of 1800 MW. Generation units data are tabulated in Appendix B [211]. Each type of emission is represented by its quadratic function, i.e. the overall objective is composed of a single fuel cost and three emissions functions. The resultant objective is formulated as follows:

$$z = [F_1(\mathbf{P}), F_2(\mathbf{P}), F_3(\mathbf{P}), F_4(\mathbf{P})] \tag{5.24}$$

where subscripts 1, 2, 3, and 4 correspond to economic cost, NO_x, SO_2, and CO_2 emissions respectively. It is assumed here that the decision maker has a Utility Function (UF) that assigns proper positive weights based on each objective importance. So the overall objective function is formulated as a constrained minimization problem as follows:

$$\mathit{Minimize}\ z = \eta_1 F_1(\mathbf{P}) + \eta_2 F_2(\mathbf{P}) + \eta_3 F_3(\mathbf{P}) + \eta_4 F_4(\mathbf{P}) \tag{5.25}$$

Subject to the equality and inequality constraints discussed earlier. Also, note that the weights are related according to $\sum_{i=1}^{K} \eta_i = 100$. The PSO Algorithm was tested as follows:

Case 1: All four functions were minimized individually and the results obtained are shown in Table 5.10. A comparison between PSO outcomes and previously published works [211] in which the Newton-Raphson method (NR) was used is tabulated in Table 5.11. It is clear that PSO found better solutions than NR in minimizing all four functions. Note that even a 1% improvement would translate to enormous annual cuts in cost and emissions.

Case 2: Each pair of objectives was combined to form a single objective function as follows:

$$\mathit{Minimize}\ z = \eta F_i + (1-\eta) F_j \ ; \ i \neq j \tag{5.26}$$

The Pareto optimal solution set is obtained in this case by changing the weight of each function as shown in Table 5.12. The shape of the Pareto optimal solution set of each pair is constructed in Figures 5.14-5-19 by obtaining a set of compromising solutions.

Each point on the curve represents an optimal or "near optimal" solution to the bi-objective optimization problem for a given weight.

Table 5.10. Individual Function Minimization

	F1	F2	F3	F4
P1(MW)	282.823506	193.659307	391.0250216	249.8915155
P2(MW)	294.6215108	210.8889282	334.687164	330.0543111
P3(MW)	468.4433957	525.7681452	556.7494734	381.7954604
P4(MW)	353.0811697	325.7273027	6.997043147	377.7313208
P5(MW)	293.0731444	476.5906814	355.0771987	341.268196
P6(MW)	216.1466775	195.7489106	283.0980479	237.3998507
F1($/h)	**18527.33624**	18767.18808	18965.92868	18580.27257
F2(kg/h)	2275.973963	**2031.287103**	3209.789854	2322.026372
F3(kg/h)	24820.63393	22917.47706	**11372.20253**	26835.39707
F4(kg/h)	58378.03426	65307.61975	82303.19414	**56473.61712**

Table 5.11. Comparison Between PSO and NR

	PSO	NR	% improvement
F1($/h)	18527.34	18721.39	1.04
F2(kg/h)	2031.29	2070.127	1.88
F3(kg/h)	11372.20	26264.86445	56.70
F4(kg/h)	56473.62	58066.35	2.74

Table 5.12. The Pareto Optimal Solution Set of Each Pair

	F1 vs. F2		F1 vs. F3		F1 vs. F4		F2 vs. F3		F2 vs. F4		F3 vs. F4	
η	F1	F2	F1	F3	F1	F4	F2	F3	F2	F4	F3	F4
0.0	18767.2	2031.3	18965.9	11372.2	18580.3	56473.6	3209.8	11372.2	2322.0	56473.6	26835.4	56473.6
0.1	18720.1	2033.8	18962.6	11372.4	18579.9	56473.6	3078.2	11378.8	2319.7	56473.7	24585.6	56593.5
0.2	18678.9	2041.0	18958.6	11373.1	18579.5	56473.7	2985.7	11394.9	2316.9	56474.3	22418.6	56977.8
0.3	18643.3	2052.9	18953.4	11374.9	18578.9	56473.9	2913.7	11418.8	2313.4	56475.5	20351.1	57669.5
0.4	18612.8	2069.3	18946.7	11378.5	18578.2	56474.3	2851.7	11452.3	2308.8	56478.0	18403.8	58721.3
0.5	18587.2	2090.3	18937.7	11386.1	18577.2	56475.1	2792.6	11501.0	2302.5	56483.2	16602.9	60199.4
0.6	18566.1	2116.0	18924.6	11402.4	18575.8	56476.9	2727.8	11581.2	2293.5	56494.4	14981.8	62187.4
0.7	18549.5	2146.8	18904.2	11441.3	18573.6	56481.1	2647.0	11734.4	2279.5	56521.1	13583.8	64794.0
0.8	18537.5	2183.1	18868.1	11555.0	18569.6	56493.7	2530.9	12096.0	2254.9	56598.7	12466.0	68165.6
0.9	18530.0	2225.7	18786.6	12070.4	18560.4	56552.0	2333.0	13318.6	2200.1	56944.3	11703.7	72527.4
1.0	18527.3	2276.0	18527.3	24820.6	18527.3	58378.0	2031.3	22917.5	2031.3	65307.6	11372.2	82303.2

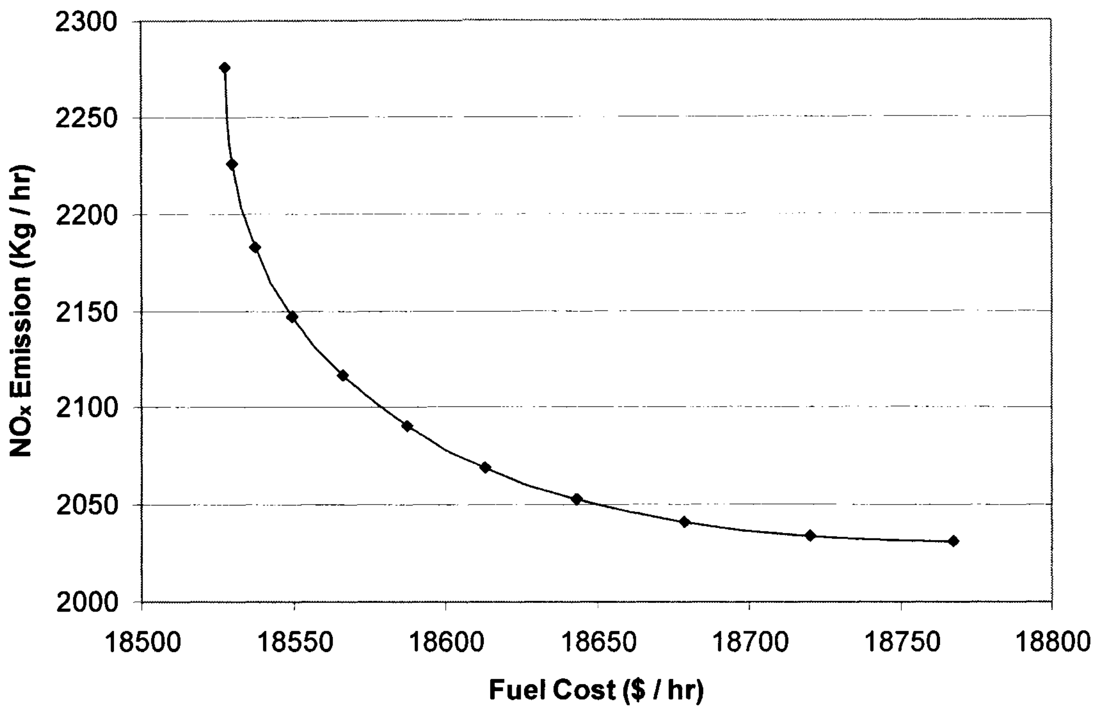

Figure 5.14. The trade-off curve between fuel cost and NO_x emission.

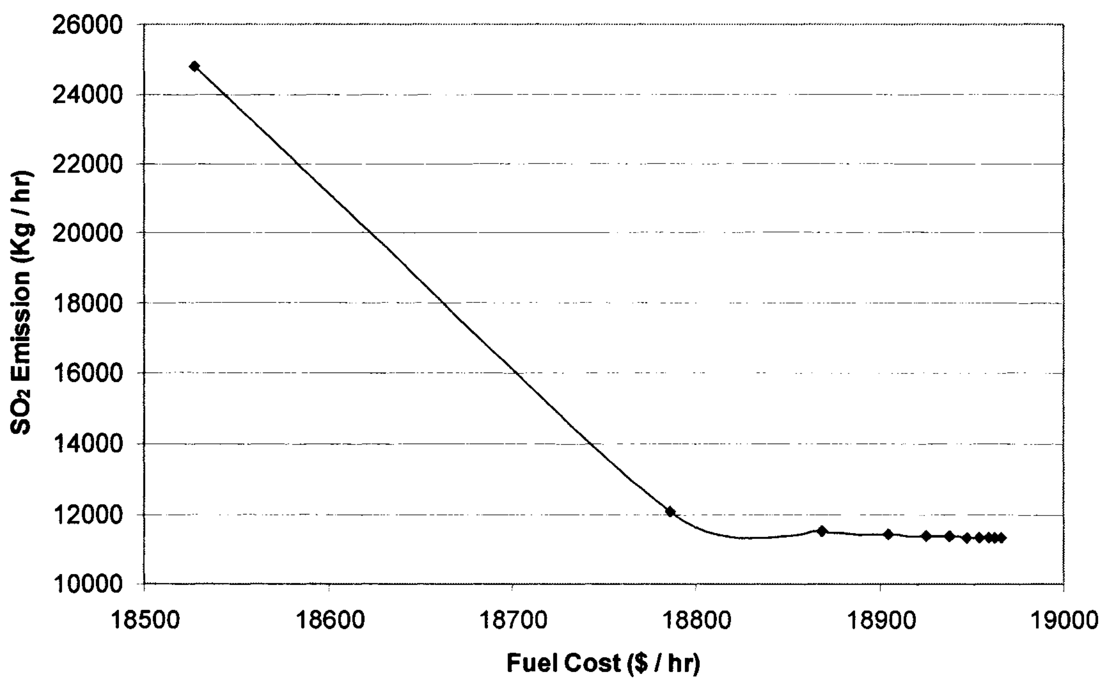

Figure 5.15. The trade-off curve between fuel cost and SO_2 emission.

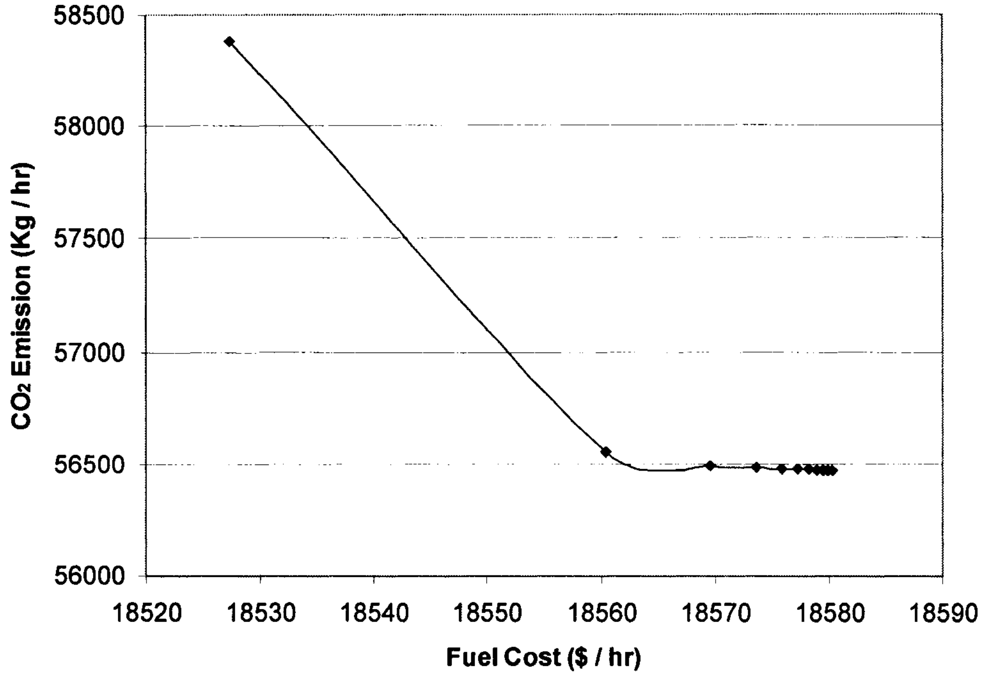

Figure 5.16. The trade-off curve between fuel cost and CO_2 emission.

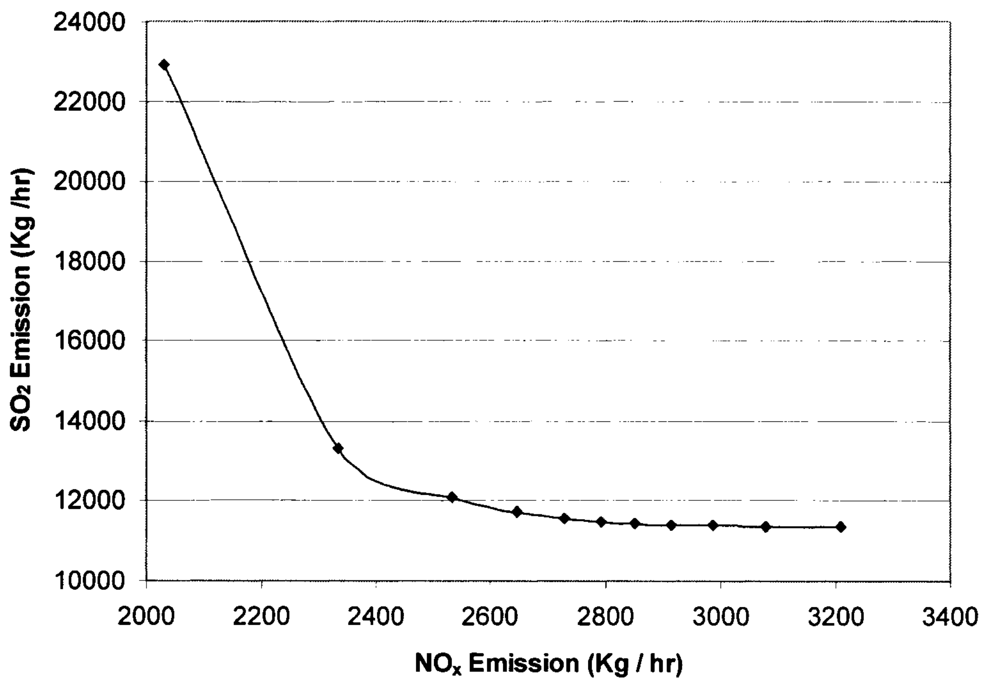

Figure 5.17. The trade-off curve between NO_x and SO_2 emission.

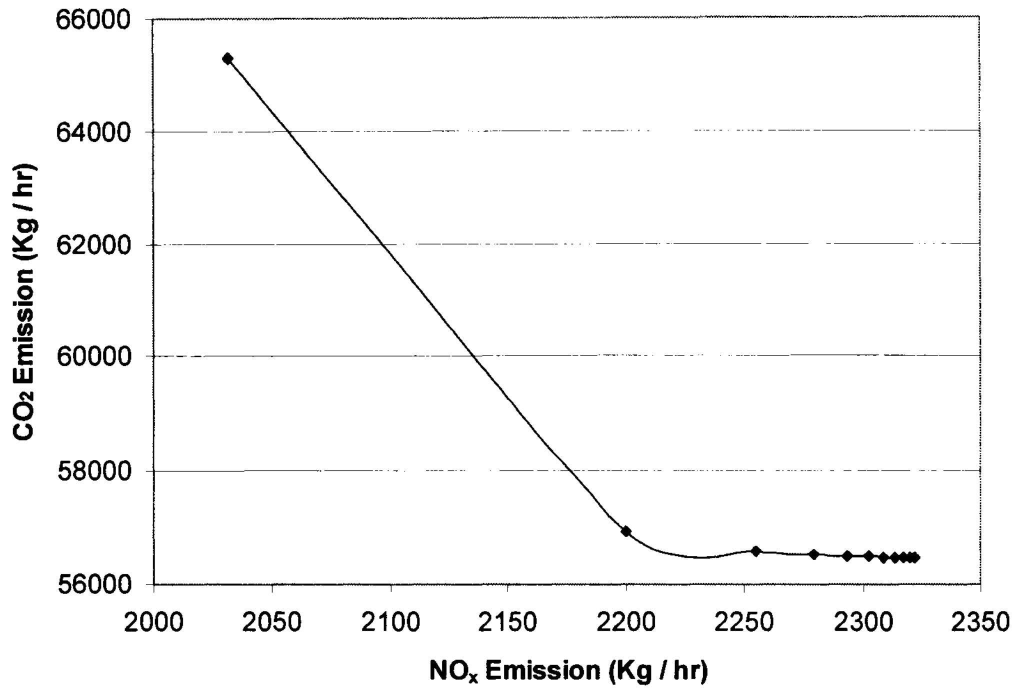

Figure 5.18. The trade-off curve between CO_2 and NO_x emission.

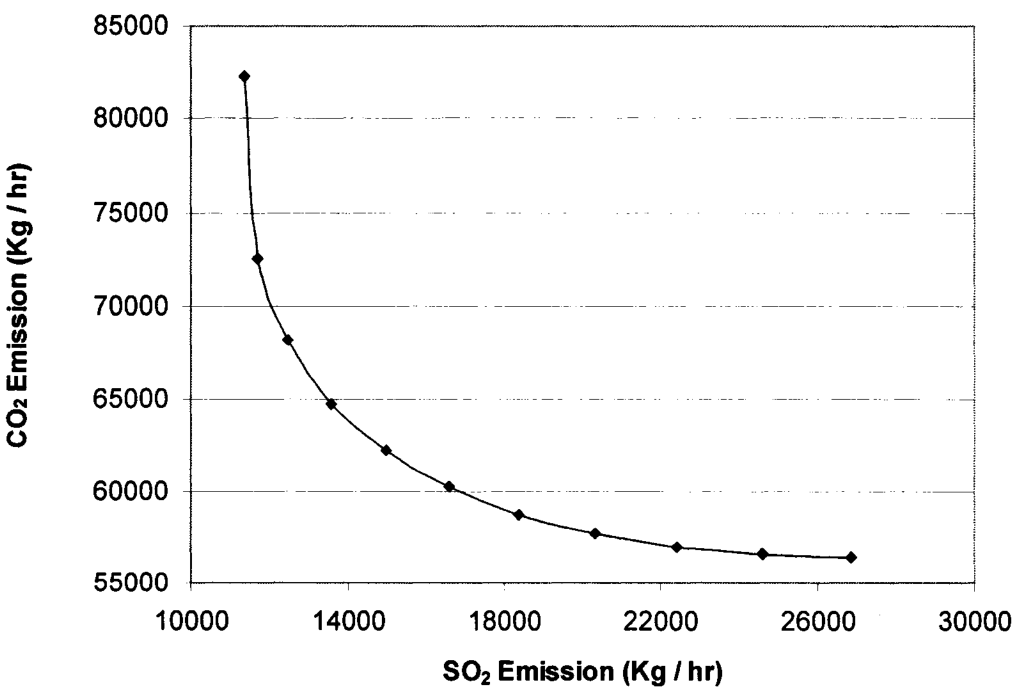

Figure 5.19. The trade-off curve between SO_2 and CO_2 emission.

Case 3: The solution of the overall multi-objective problem was achieved by minimizing the decision maker UF with the following three scenarios:

A. All functions have equal weights, i.e. 25.

B. With assigned weights of 40, 30, 20, and 10 to F_1, F_2, F_3, and F_4 respectively.

C. With assigned weights of 60, 20, 10, and 10 to F_1, F_2, F_3, and F_4 respectively.

Results are summarized in Table 5.13. The findings are compared to results found in [211] as shown in Table 5.14. Table 5.14 clearly signifies the success of PSO algorithm in solving this problem when compared to traditional methods.

In analyzing the two methods used in combining the multi-objective optimization problem, namely using the price penalty factor and weight factor method, one can conclude that these two methods work exactly in the same manner. Each point on the curve represents an optimal or "near optimal" solution to the multi-objective optimization problem for a given price or weight factor. Different results between the two methods are mainly due to the factors chosen during the analysis. PSO was able to capture the shape of the Pareto solution set when both methods were used.

Table 5.13. Overall UF Minimization

	A	B	C
P1(MW)	270.99	279.19	271.53
P2(MW)	352.90	350.52	341.19
P3(MW)	438.63	467.90	446.72
P4(MW)	226.92	176.26	237.65
P5(MW)	381.64	394.74	373.82
P6(MW)	251.55	256.20	249.24
P_L(MW)	122.62	124.81	120.16
F1($/h)	18639.30	18689.01	18615.73
F2(kg/h)	2360.12	2432.25	2323.54
F3(kg/h)	16837.94	14620.07	17372.29
F4(kg/h)	59983.19	62856.00	59580.62
UF	2445513.81	1741489.39	1932943.76

Table 5.14. Comparison Between PSO and NR

	Objective	A	B	C
PSO	F1($/h)	18639.3	18689.0	18615.7
	F2(kg/h)	2360.1	2432.2	2323.5
	F3(kg/h)	16837.9	14620.1	17372.3
	F4(kg/h)	59983.2	62856.0	59580.6
	UF	2445513.8	1741489.4	1932943.8
NR	F1($/h)	18772.6	18848.9	18837.9
	F2(kg/h)	2339.3	2424.7	2412.4
	F3(kg/h)	27209.0	27752.9	27699.9
	F4(kg/h)	58112.4	58348.4	58262.3
	UF	2660833.0	1965238.4	2038145.6

It is worth mentioning at this point that the PSO algorithm is very inexpensive in terms of computation time and memory usage. All program runs performed during simulation took about 0.1-0.2 seconds to complete a total of 800 iterations. Throughout this research, PSO would converge to a "good" solution within the first 100 iterations. Then slow improvements would follow to enhance the accuracy of its solution.

5.7 Summary

The ECD and ED problems are formulated separately at first, then they were combined to form the EED. This problem has been getting more attention recently due to the deregulation of the power industry and strict environmental regulations. It is formulated as a highly nonlinear constrained multi-objective optimization problem with conflicting objectives. A PSO technique was developed and presented as an effective tool for solving multi-objective optimization problems like the EED. A novel equality constraint handling mechanism is proposed in this chapter to ensure satisfaction of the equality constraints throughout the optimization process without the need to use penalty factors. PSO was tested using three standard test systems. Results demonstrated its effectiveness and robustness in finding optimal or near optimal solution sets when compared to other widely used techniques and software. It was shown that PSO was successfully capable of capturing the shape of Pareto solution sets. Also comparison of methods in combining multi-objective optimization problems into a single objective was presented. This technique is further extended to handle more than two objectives. Computation time, simplicity, and its capabilities of handling a wide class of optimization problems are key advantages of this powerful heuristic technique.

Chapter 6

Optimal Power Flow

6.1 Introduction

Electric power grids are considered the most complex man-made systems mainly due to their wide geographical coverage, various transactions among different utilities, and diversity in individual electric power companies' layouts, size, and equipment used. Engineers need special tools to optimally analyze, monitor, and control different aspects of such sophisticated systems. Some of these tools are economic dispatch, unit commitment, state estimation, automatic generation control, security analysis, and OPF. The latter is regarded as the backbone tool that has been extensively researched since its first introduction in the early 1960's [214;215]. It appears that the term "optimal power flow" was first introduced by Dommel and Tinney in 1968 [216].

Initially, the OPF was formulated as a natural extension of the traditional economic dispatch. Differences between the two optimization functions exist even though both of them may share the same objective function. In economic dispatch, the entire power network is reduced to a single equality constraint. By contrast, all major elements of the modeled system are explicitly presented in the OPF problem. The generic term "OPF" is no longer associated exclusively with the extended economic dispatch calculation. Rather, it presents a wide range of optimization problems commonly formulated in power systems related studies. The historical development of the OPF is closely correlated with the advances made in the area of numerical optimization techniques [217]. Researchers have attempted to apply most optimization techniques to solve the OPF.

The goal of OPF is to find the optimal settings of a given power system network that optimize a certain objective function while satisfying its power flow equations, system security, and equipment operating limits. Different control variables are manipulated to achieve an optimal network setting based on the problem formulation. The main control variables typically used in optimizing the OPF are as follows:

1. Generators' real power outputs and voltages.
2. Transformer tap changing settings.
3. Phase shifters settings and placement for expansion planning.
4. Switched capacitors and reactors.
5. FACTS devices settings and placement for expansion planning.

A major difficulty of the OPF problem is the nature of the control variables since some of them are continuous (e.g. real power outputs and voltages) and others are discrete (e.g. transformer tap setting, phase shifters, and reactive injections). The presence of discrete variables makes the optimization problem a non-convex one, which in turn complicates the solution methodology. The most commonly used objective is the minimization of the overall fuel cost function (convex and non-convex). However, other traditional objectives are as follows:

1. Minimization of active power loss.
2. Bus voltage deviation.
3. Emission of generating units.
4. Number of control actions.
5. Load shedding.
6. Transient stability index.
7. Capacity of transmission lines.
8. Post-contingency correction time.

Deregulation of the electric power industry has also introduced new objectives to the OPF problem such as:

1. Maximization of the social welfare.
2. Individual supplier's profit.

3. Bidding strategy.
4. Wheeling rates.

Researchers proposed different mathematical formulations of the OPF problem, which can be broadly classified as follows:

1. Linear problem in which objectives and constraints are given in linear forms with continuous control variables.
2. Non-linear problem where either objectives or constraints or both combined are non-linear with continuous control variables.
3. Mixed integer linear and non-linear problems when control variables are both discrete and continuous.

Various traditional optimization techniques were developed to solve the OPF problem, the most popular being linear programming, sequential quadratic programming, the generalized reduced gradient method, and the Newton method. The reader is referred to references [2;3;139] for a complete list of the most commonly used conventional optimization algorithms with regard to the OPF. Despite the fact that some of these techniques have excellent convergence characteristics and various among them are widely used in the industry, some of their drawbacks are:

1. They are local optimizers in nature, i.e. they might converge to local solutions instead of global ones if the initial guess happens to be in the neighborhood of a local solution. This occurs as a result of using Kuhn-Tucker conditions as termination criteria to detect stationary points. This practice is commonly used in most commercial nonlinear optimization programs [11].
2. Each technique is tailored to suit a specific OPF optimization problem based on the mathematical nature of the objectives and/or constraints.
3. The theoretical assumptions behind these developed algorithms may not be suitable for the actual OPF conditions like convexity, differentiability, and continuity, among other things.

PSO is one of the new optimizers that have been investigated to solve the OPF problem. Researchers in references [42;72;73] have attempted to utilize the PSO to solve the OPF problem considering different objective functions. In their mathematical formulation, only continuous control settings were considered as optimization variables which restrict its applicability to real power systems. In a different formulation, authors in references [70;71;145] employed the PSO to solve the OPF with the inclusion of both discrete and continuous optimization variables. Then, they augmented the OPF objective function by adding penalty terms to transform the constrained OPF into an unconstrained one. This approach usually encounters a major difficulty in properly selecting penalty factor values. If the penalty factors selected are high, the optimization algorithm will get trapped in local solutions. On the other hand, the algorithm may not be able to detect a feasible solution if the penalty factors are low [42;216].

6.2 Problem Formulation

The OPF goal is to optimize a certain objective subject to several equality and inequality constraints. The problem can be mathematically modeled as follows:

$$Min \quad F(x,u) \tag{6.1}$$

Subject to

$$g(x,u)=0 \tag{6.2}$$

$$h_{\min} \le h(x,u) \le h_{\max} \tag{6.3}$$

where the vector x denotes the state variables of a power system network at one point of time that contains the slack bus real power output (P_{G1}), voltage magnitudes and phase angles of the load buses (V_{Lk}, θ_{Lk}), and generator reactive power outputs (Q_G). Vector u represents both integer and continuous control variables that consist of real power generation levels (P_{GN}) and voltage magnitudes $\left(|V_{GN}|\right)$, transformer tap settings (T_k), and reactive power injections (Q_{Ck}) due to volt-amperes reactive (VAR) compensators; i.e.

$$u=\left[\overbrace{P_{G2}\ldots P_{GN}, V_{G2}\ldots V_{GN}}^{Continuous}, \overbrace{T_1\ldots T_N, Q_{C1}\ldots Q_{CN}}^{Discrete}\right] \tag{6.4}$$

6.2.1 Objective Functions

In this study, minimization of different objectives is considered to examine the performance of the proposed algorithm. The objective functions taken into considerations are fuel emission, fuel cost, and the network real power losses. Each objective is briefly described as follows:

1. **Fuel Emission:**

Fossil based thermal plants are considered to be a major player in the pollution crisis that we are facing nowadays. Industrial growth led to greater demands to generate more electricity. Consequently, the emission of these generating units is gradually building up in the atmosphere which is having a severe impact on our environment. One way to cope with this problem is to dispatch electric power with emission considerations. The objective of the fuel emission dispatch problem is to minimize the total emission of all thermal units by allocating optimal control settings while satisfying various network operation constraints. Fuel emission of a number of generating units can be modeled mathematically as follows:

$$E = \sum_{i=1}^{N} (\alpha_i + \beta_i P_i + \gamma_i P_i^2) \text{ ton/hr} \tag{6.5}$$

2. **Fuel Cost:**

The aim of the fuel cost dispatch problem is to allocate the best network settings that minimize the overall fuel cost function while imposing all network constraints. Conventionally, the overall fuel cost function for a number of thermal generating units can be modeled by a quadratic function (convex and differentiable) as follows:

$$F = \sum_{i=1}^{i=N} (a_i + b_i P_i + c_i P_i^2) \text{ \$/hr} \tag{6.6}$$

However, this model ignores the valve point loading due to throttling losses caused by partial valve opening that introduces rippling effects to the actual input-output curve. In typical steam turbine-generators, multiple control valves are used for steam admission.

This usage of multiple valves improves the turbine efficiency for all output levels when compared to using a single control valve [218]. Equation (6.6) is modified by adding an additional sine term to account for the valve effects in this manner [219]:

$$F = \sum_{i=1}^{i=N}\left[a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin(f_i (P_i^{\min} - P_i)) \right| \right] \text{ \$/hr} \tag{6.7}$$

This more accurate modeling adds more challenges to most derivative-based optimization algorithms in finding the global solution since the objective is no longer convex nor differentiable everywhere. Figure 6.1 shows the shape of the fuel cost function with the valve loading effects included. This more accurate modeling may have great economical advantages for any power utility. An estimate annual saving of $60,000 was reported for the Philadelphia Electric Company when their steam system operations were based on valve-point loading [220]. This study was done in 1962 and it is based on a total generation capacity of 3256 MW.

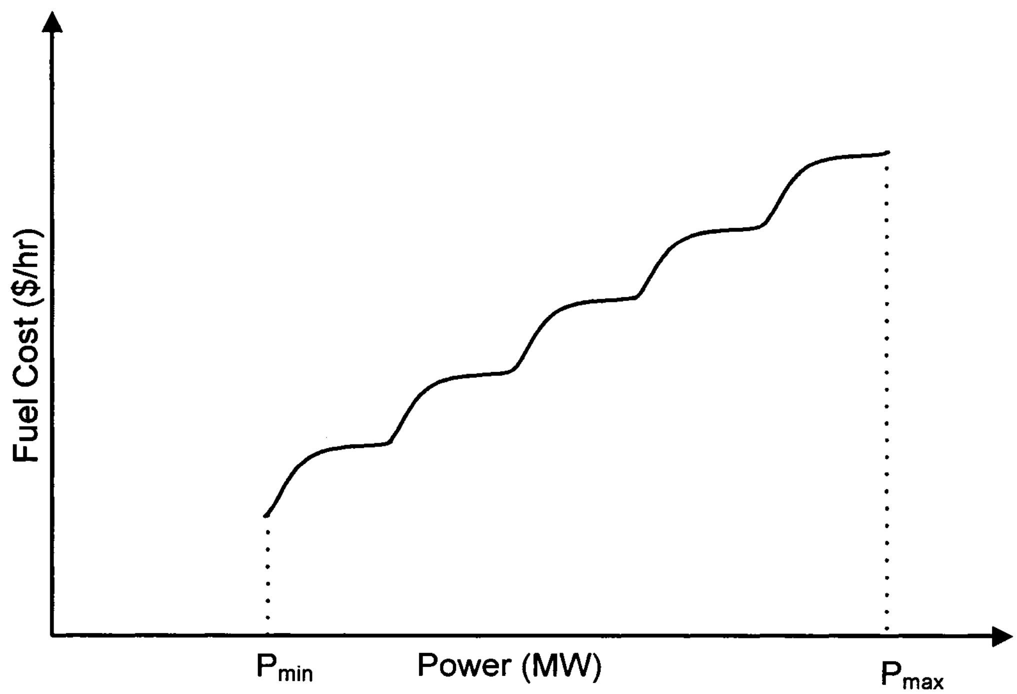

Figure 6.1. The generator input-output curve considering the valve point effects.

3. Real Power Losses:

With this objective, all control settings are adjusted such that the total real power losses are minimized. Power losses can be modeled as follows:

$$P_L = \sum_{k=1}^{N_L} g_k \left[|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos(\delta_i - \delta_j) \right] \tag{6.8}$$

where N_L is the number of transmission lines in the system, g_k is the conductance of the line k connecting buses i and j, and the bus voltage is represented in polar form by $|V|$ and δ.

6.2.2 Constraints

The OPF problem has two categories of constraints:

1) Equality Constraints:

These are the sets of nonlinear power flow equations that govern the power system, i.e.

$$P_{G_i} - P_{D_i} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) = 0 \tag{6.9}$$

$$Q_{G_i} - Q_{D_i} + \sum_{j=1}^{n} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) = 0 \tag{6.10}$$

where P_{Gi} and Q_{Gi} are the real and reactive power outputs injected at bus i respectively, the load demand at the same bus is represented by P_{Di} and Q_{Di}, and elements of the bus admittance matrix are represented by $|Y_{ij}|$ and θ_{ij}.

2) Inequality Constraints:

These are the set of continuous and discrete constraints that represent the system operational and security limits like the bounds on:

1. The generators real and reactive power outputs;

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max},\ i = 1,\ldots,G_N \tag{6.11}$$

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max},\ i = 1,\ldots,G_N \tag{6.12}$$

2. Voltage magnitudes at each bus in the network;

$$V_i^{\min} \leq V_i \leq V_i^{\max},\ i = 1,\ldots,N \tag{6.13}$$

3. The discrete transformer tap settings;

$$T_i^{\min} \leq T_i \leq T_i^{\max},\ i = 1,\ldots,T_N \tag{6.14}$$

4. The discrete reactive power injections due to capacitor banks;

$$Q_{C_i}^{\min} \leq Q_{C_i} \leq Q_{C_i}^{\max},\ i = 1,\ldots,C_N \tag{6.15}$$

Note that P_{Gi}, Q_{Gi}, and V_i are continuous variables while T_i and Q_{Ci} are discrete ones.

5. The transmission lines loading;

$$S_{L_i} \leq S_{L_i}^{\max},\ i = 1,\ldots,L_N \tag{6.16}$$

A hybrid method is developed to solve these OPF problems and it is detailed in the following section.

6.3 The Proposed Hybrid Algorithm

The proposed hybrid approach combines PSO technique with the Newton-Raphson based power flow program in which the former technique is used as a global optimizer to find the best combinations of the mixed type control variables while, the latter serves as a minimizer to reduce the nonlinear power flow equations mismatch. The Newton-Raphson method used in this implementation is the one with the full Jacobian evaluated and updated at each iteration. The hybrid PSO (HPSO) utilizes a population of particles or possible solutions to explore the feasible solution hyperspace in its search for an optimal solution. Each particle's position is used as a feasible initial guess for the power flow subroutine. This mechanism of multiple initial solutions can provide better probability of detecting an optimal solution to the power flow equations that would globally minimize a given objective function. The importance of such hybridization is signified by realizing the fact that in a transmission system, the solution to the power flow equation is not unique, i.e. multiple solutions within the stability margins may exist and only one can globally optimize a certain objective [221]. The flow chart of the proposed algorithm is shown in Figure 6.2.

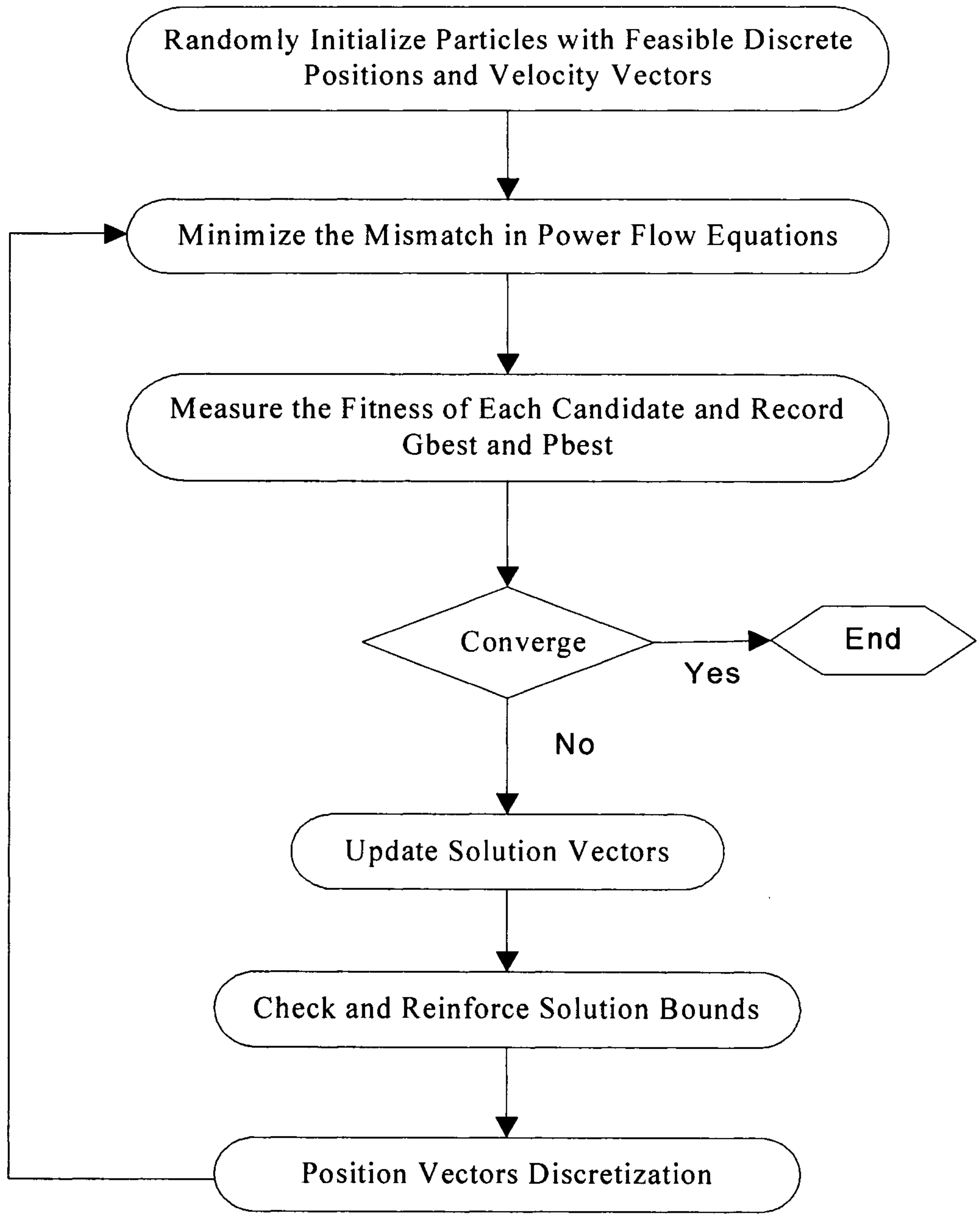

Figure 6.2. Flow chart diagram of the proposed algorithm.

6.3.1 Constraints Handling Methods

Various methods were proposed to handle problem constraints within the context of evolutionary computation methods. A brief description of the main constraint handling mechanisms is highlighted in chapter 3. Within the context of PSO applications to the OPF and economic dispatch, inequality constraints that represent the permissible operating range of each optimization variable are typically handled in one of the following two ways:

- Set to Limit Approach (SLA): If any optimization variable exceeds its upper or lower bound, the value of the variable is set to the violated limit. This resembles the idea found in operating all generating units at equal incremental production costs to reach optimal power dispatch. Once any unit violates its operating range, the real power is set to the violated limit. It is important to note that PSO has some randomness in the update equation that might cause several variables to exceed their limits during the optimization process. Thus, this approach may fix multiple optimization variables to their operating limits for which global solution may not be reached. Also this approach fails to utilize the memory element that each particle has once it exceeds its boundaries. References [28;31;74;75] employ this approach.
- Penalty factor: The other approach is to use penalty factors to incorporate the inequality constraints into the objective. The main problem with this approach is introducing new parameters that need to be properly selected in order to reach acceptable PSO performance. Values of the penalty factors are problem dependant, thus this approach requires proper adjustments of the penalty factors in addition to tuning the PSO parameters. References [70;71;73] make use of this approach.

6.3.2 Hybrid Inequality Constraints Handling Mechanism

The inequality constraints are handled by a hybrid constraints handling mechanism that brings together the concepts of two common methods currently used in evolutionary computation optimization methods to deal with constraints. It combines the ideas of preserving feasible solutions and infeasible solution rejection methods to retain only feasible solutions throughout the optimization process without the need to introduce penalty factors in the objective function. In most of the evolutionary computation optimization methods that employ the infeasible solution rejection method to handle constraints, any solution candidate among the population is randomly re-initialized once it crosses the boundaries of the feasible region. The majority of these methods do not have memory elements associated with each candidate in the population. However, in the cases of HPSO in which each particle has a memory element (*pbest*) that recalls the best visited location through its own flying experience to search for the optimal solution and may use this information once it violates the problem boundaries. Thus, this hybridization makes use of the memory element that each particle has to maintain its feasibility status. This restoration operation keeps the infeasible particle *alive* as a possible candidate that could locate the optimal solution instead of completely rejecting it and therefore eliminating its potential in the swarm.

6.3.3 Control Variables Treatment

The problem variables considered in this formulation are of two types: continuous and discrete, as shown in Equation (6.4), that require special initialization and treatment of the position vector throughout the optimization process. The continuous variables are initialized with uniformly distributed pseudorandom numbers that take the range of these variables, e.g. $P_i = random[P_i^{min}, P_i^{max}]$ and $V_i = random[V_i^{min}, V_i^{max}]$. However, in the case of the discrete variables, an additional operator is needed to account for the distinct nature of these variables. A rounding operator is included to ensure that each discrete variable is rounded to its nearest decimal integer value that represents the physical operating constraint of a given variable. Each transformer tap setting is rounded to its nearest decimal integer value of 0.01 by utilizing the rounding operator as follows $round(random[T_i^{min}, T_i^{max}], 0.01)$. The same principle applies to the discrete reactive injection due to capacitor banks with the difference being the step size, i.e. $round(random[Q_{Ci}^{min}, Q_{Ci}^{max}], 1)$. This ensures that the fitness of each solution is measured only when all elements of the solution vector are properly represented to reflect the real world nature of each variable. Since the particle update equations have some uniformly distributed random operators built into them and because of the addition of two different types of vectors, the rounding operator is called again after each update to act only on the discrete variables as follows: $round(T_i, 0.01)$ and $round(Q_{Ci}, 1)$. Once the rounding process is over, all solution elements go through a feasibility check. This simple rounding method guarantees that power flow calculations and fitness measurements are obtained only when all problem variables are properly addressed and their nature types are accounted for.

6.4 Simulation and Results

The proposed algorithm was implemented in the Matlab® computing environment and the standard IEEE 30-bus test system was used to validate its potential. The test system consists of six generating units interconnected with 41 branches of a transmission network to serve a total load of 189.2 MW and 107.2 Mvar as shown in Figure 6.3. A detailed description of the system's data is presented in the Appendix C [9;222]. The emission data used in this study are for nitrogen oxides (NO_X). However, the proposed algorithm can easily accommodate other types of emissions. Note that the original system has two capacitor banks installed at bus 5 and 24, with ratings of 19 and 4 Mvar respectively. A series of experiments was conducted to properly tune the HPSO parameters to suit the targeted OPF problem. Considering the quadratic fuel cost function as an objective, Figures 6.4-6.6 show the HPSO outcomes as a result of varying each parameter. Table 6.1 summarizes results from this early tuning process. To quantify the results, 50 independent runs were executed for each parameter variation. The most noticeable observation from this groundwork is that the optimal settings for c_1 and c_2 are found to be 1.0. These values are relatively small since most of the values reported in the previously related work are in the range of 1.4-2 [28;31;70;74;75]. The best settings for number of particles and particle's maximum velocity (V_{max}) are 20 and 0.1 respectively.

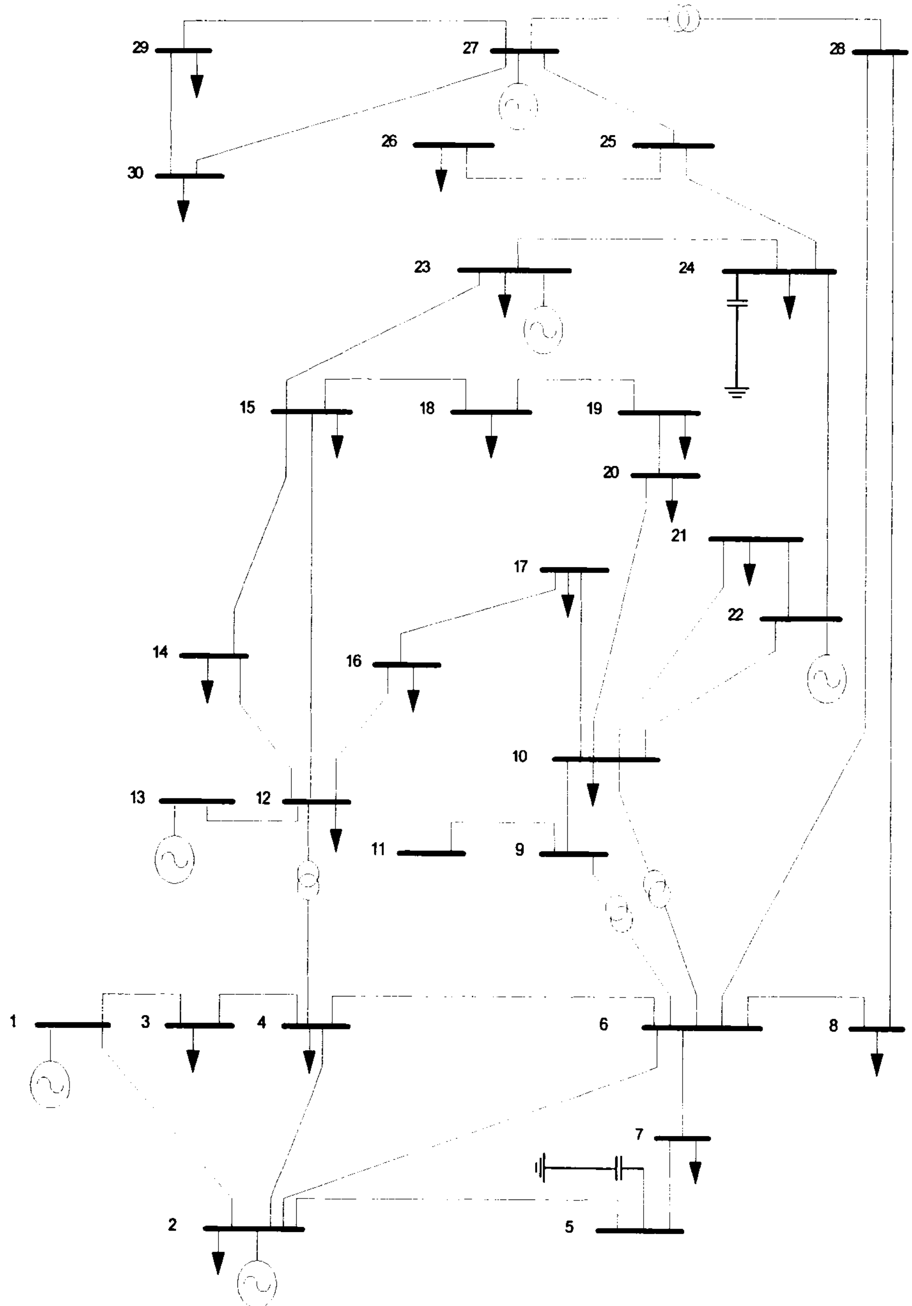

Figure 6.3. A single line diagram of IEEE 30-bus standard test system.

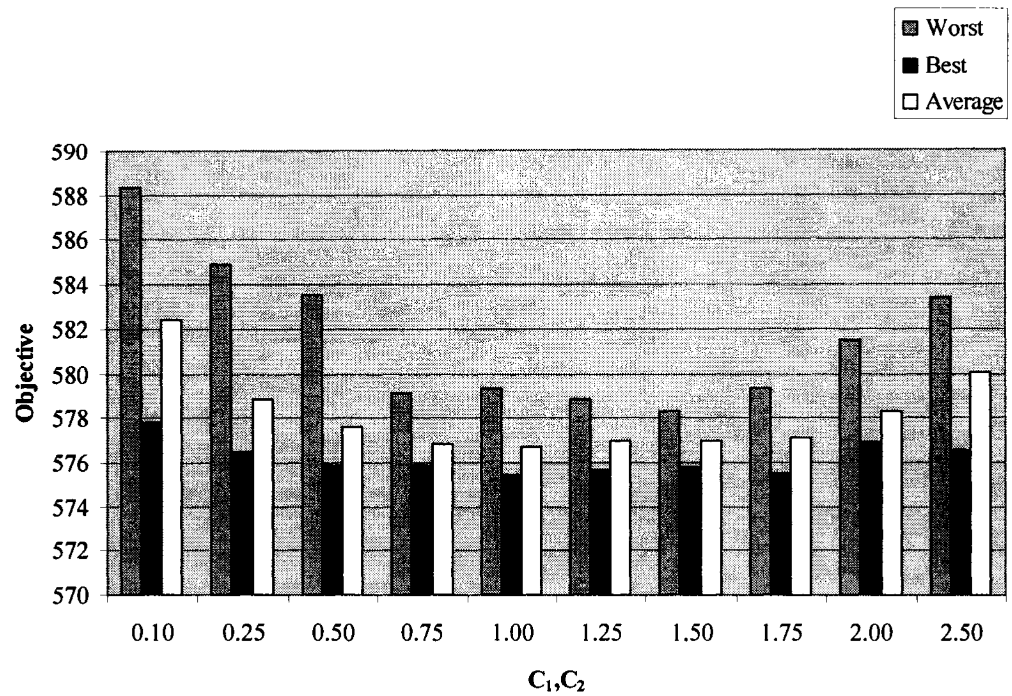

Figure 6.4. Impact of the acceleration constants on the convergence characteristic.

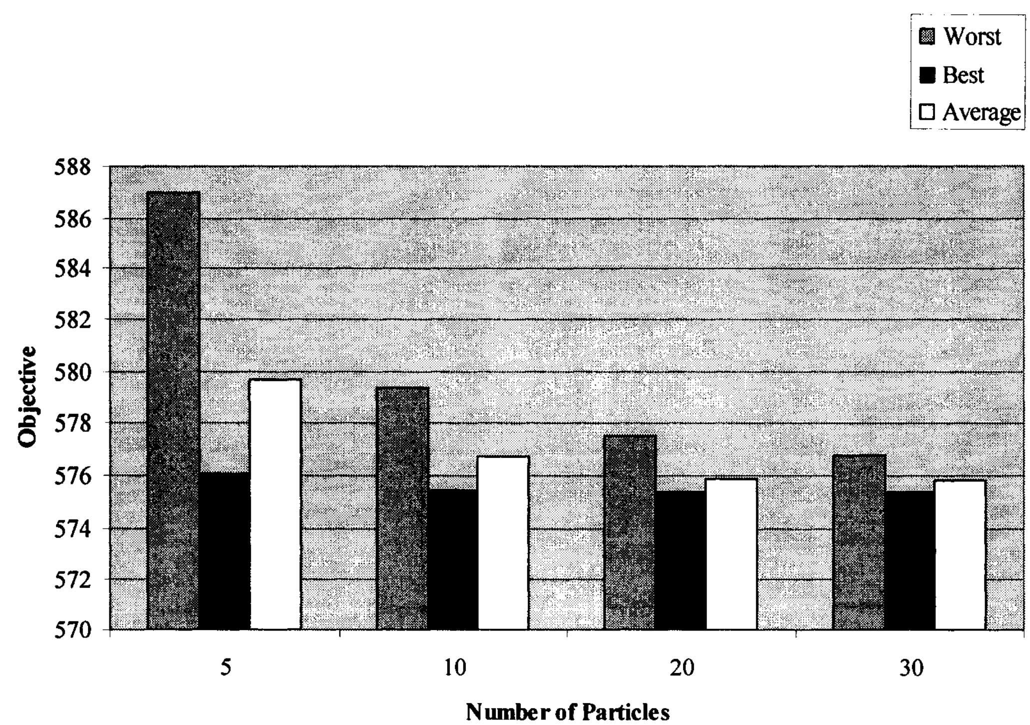

Figure 6.5. Impact of the swarm size on the convergence characteristic.

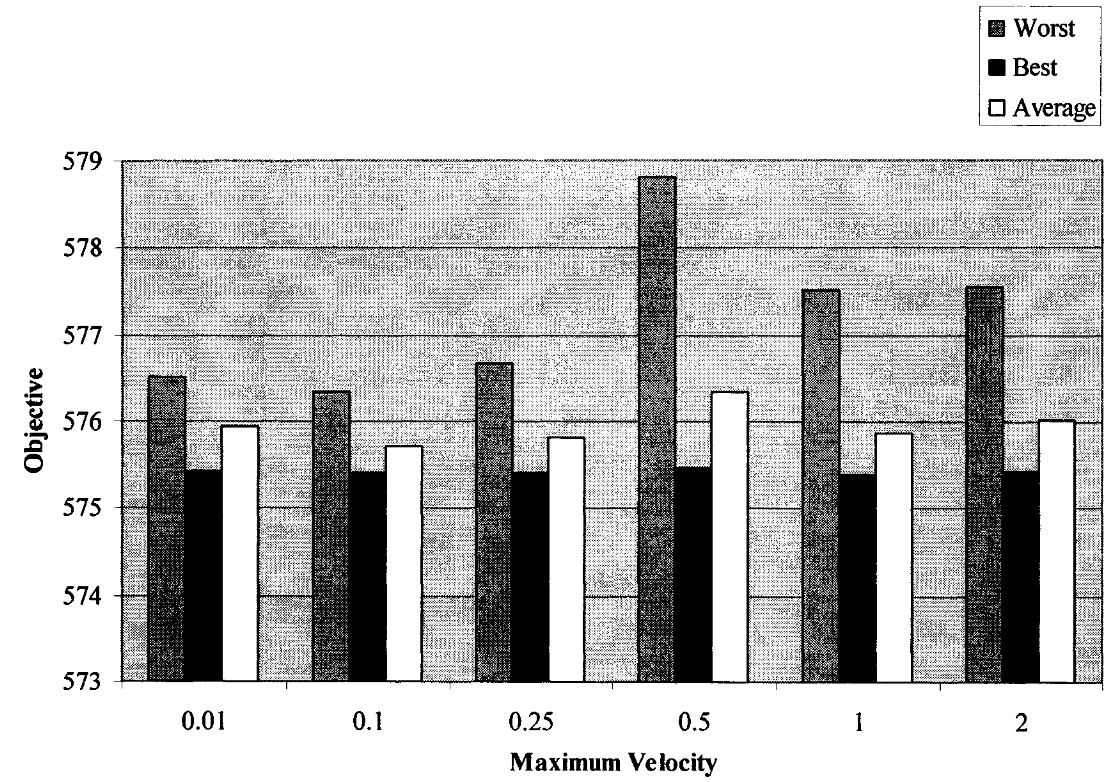

Figure 6.6. Impact of the maximum velocity on the convergence characteristic.

In this implementation, V_{max} is the upper limit used to randomly initialize and enforce the velocity vector throughout the optimization process. A fixed V_{max} value is used for all problem variables. This means that the velocity vector of all optimization problems is randomly initialized with a range of $[-V_{max}, V_{max}]$. It appears from the results shown in Table 6.1 that HPSO performed better with lower values of V_{max}. In addition, the proposed algorithm incorporates an inertia weight with linearly decreasing function as discussed in chapter 3 to provide better control on balancing exploration and exploitation by controlling the velocity vector update equation. This parameter directly impacts the velocity vector with larger values in the early stage of the search process and lower values toward the end of the iterations. In the presence of the inertia weight parameter, proper setting of V_{max} would take the least priority when compared to setting the acceleration constants or swarm's size. Note that increasing the number of particles beyond 20 will improve the solution accuracy slightly at the expense of increasing the computation time significantly.

Table 6.1. A Study of Tuning HPSO Parameters

Parameter		Ave	Min	Max	St. Dev.	Other HPSO Parameters
C_1,C_2	0.10	582.396	577.831	588.311	2.950	No. of Particle = 10
	0.25	578.845	576.501	584.893	2.220	Max. Velocity = 1
	0.50	577.569	575.835	583.552	1.761	Max. Iterations =30
	0.75	576.849	575.841	579.132	0.921	
	1.00	**576.721**	**575.461**	**579.343**	**0.931**	
	1.25	576.971	575.659	578.876	0.932	
	1.50	576.939	575.809	578.321	0.935	
	1.75	577.129	575.526	579.325	0.941	
	2.00	578.266	576.882	581.483	1.201	
	2.50	580.053	576.583	583.388	1.977	
Number of Particles	5	579.679	576.086	586.938	2.910	$C_1 = C_2 = 1.0$
	10	576.721	575.461	579.343	0.931	Max. Velocity = 1
	20	**575.872**	**575.392**	**577.514**	**0.521**	Max. Iterations =30
	30	575.792	575.392	576.788	0.351	
Maximum Velocity	0.01	575.949	575.418	576.518	0.356	$C_1 = C_2 = 1.0$
	0.1	**575.704**	**575.411**	**576.339**	**0.263**	No. of Particle = 20
	0.25	575.811	575.414	576.678	0.343	Max. Iterations =30
	0.5	576.344	575.456	578.814	1.065	
	1	575.872	575.392	577.514	0.521	
	2	576.025	575.424	577.553	0.564	

The inertia weight is kept fixed throughout the simulation process between the upper and lower bounds of 0.9 and 0.4 respectively since changing its values did not have a great impact on improving the convergence characteristics. The same parameters were suitable for Cases 1 and 2 below. Once the HPSO best parameters were set, the following cases were considered to test the proposed approach:

Case 1: The quadratic emission and fuel cost functions in Equations (6.5) and (6.6) were minimized considering only the continuous control variables, i.e. real power outputs and voltages at voltage-controlled buses. A comparison of results obtained using the HPSO to those obtained using MATPOWER, MATLAB-based software that uses SQP to solve the

OPF, are shown in Table 6.2. MATPOWER is capable of solving the OPF when the objective is represented in polynomial form and is only capable of handling continuous variables. SQP took 28 evaluations of fuel cost and emission functions to converge to its answer while in HPSO each particle is evaluated 30 times. Results clearly indicate that HPSO achieved better solution in both cases when only continuous optimization variables are used.

Table 6.2. Comparison Between HPSO and SQP for Case 1

	Fuel Cost ($/hr)		Emission (ton/hr)	
Method	SQP	PSO	SQP	PSO
P_{g1}	41.54	43.611	24.88	24.016
P_{g2}	55.4	58.060	28.82	27.601
P_{g13}	16.2	17.555	33.05	30.181
P_{g22}	22.74	22.998	33.06	34.441
P_{g23}	16.27	17.056	26.25	30.000
P_{g27}	39.91	32.567	45.27	45.202
V_1	0.982	1.000	1.033	1.000
V_2	0.979	1.000	1.03	1.001
V_{13}	1.064	1.059	1.1	1.064
V_{22}	1.016	1.012	1.023	1.023
V_{23}	1.026	1.021	1.054	1.043
V_{27}	1.069	1.037	1.068	1.048
Objective	576.892	575.411	284.966	282.628
P_{losses}	2.860	2.647	2.130	2.240

<u>**Case 2:**</u> The test system is modified by introducing four tap-changing transformers between buses 6-9, 6-10, 4-12, and 27-28. The operating range of all transformers is set between 0.9-1.05 with a discrete step size of 0.01. The capacitor banks at buses 5 and 24 are also considered as new discrete control variables with a range of 0-40 Mvar and a step size of 1. With this modification, the problem now has both continuous and discrete

control variables that can be troublesome to most conventional optimization methods. In addition to the objectives considered in Case 1, the total real power losses are also introduced as a new objective in this case. Table 6.3 summarizes the results of each minimization problem along with the best solution vector achieved. The inclusion of discrete variables in this case further improved the results of minimizing the fuel cost and emission functions when compared to Case 1. The convergence characteristic of each objective is shown in Figures 6.7-6.9. The HPSO algorithm appears to converge fast in the early iterations then further improvements are progressed before reaching the stopping criteria.

Table 6.3. Results of Different Objective Minimization When Both Discrete and Continuous Variables are Considered (Case 2)

	Fuel Cost (\$/hr)	Emission (ton/hr)	P_{losses} (MW)
P_{g1}	42.180	24.032	7.057
P_{g2}	57.013	27.333	50.131
P_{g13}	17.305	29.817	39.888
P_{g22}	22.025	33.895	45.575
P_{g23}	17.872	29.993	19.116
P_{g27}	35.060	46.202	28.963
V_1	1.000	1.000	1.000
V_2	0.999	1.002	0.950
V_{13}	1.061	1.098	1.100
V_{22}	1.071	1.041	1.091
V_{23}	1.076	1.073	1.093
V_{27}	1.100	1.084	1.093
Q_{C5}	4.000	2.000	9.000
Q_{C24}	8.000	9.000	9.000
$T_{6\text{-}9}$	0.900	0.970	0.900
$T_{6\text{-}10}$	0.950	0.930	0.950
$T_{4\text{-}12}$	0.930	1.020	0.920
$T_{27\text{-}28}$	0.950	0.990	0.980
Objective	574.143	282.218	1.540

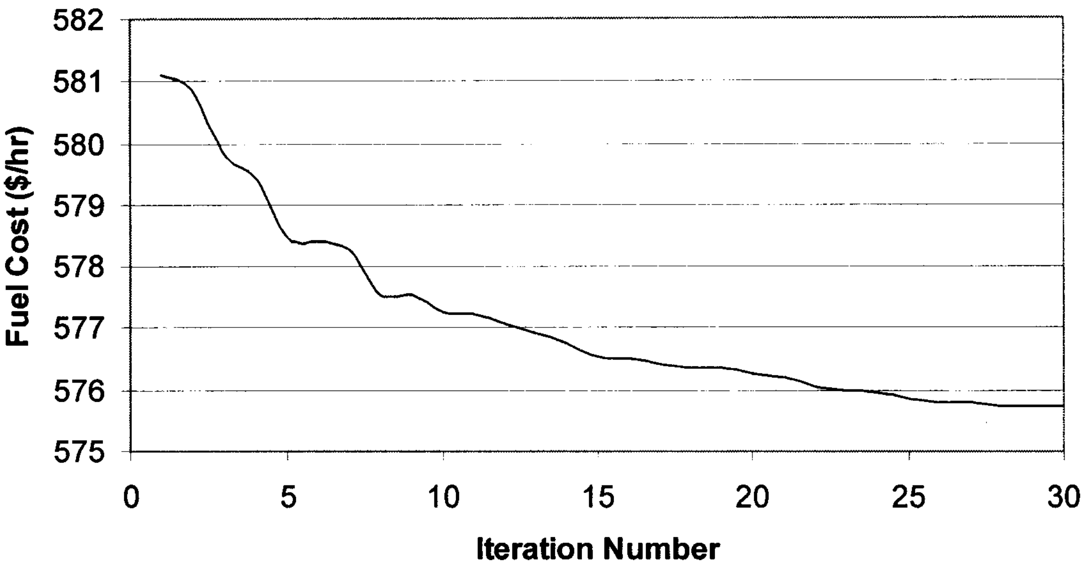

Figure 6.7. Convergence characteristic of the proposed approach in minimizing the fuel cost.

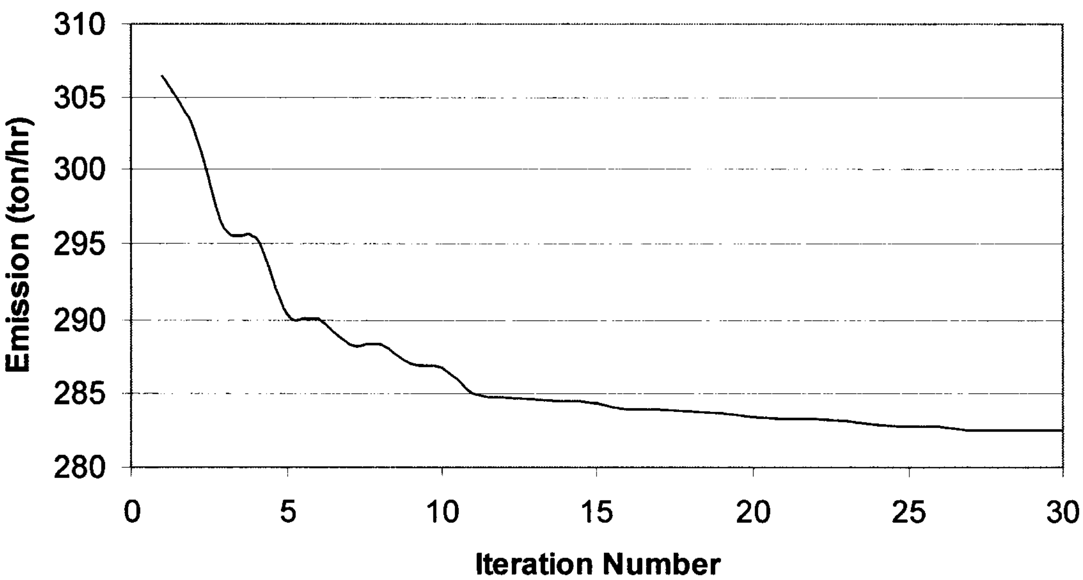

Figure 6.8. Convergence characteristic of the proposed approach in minimizing the emission.

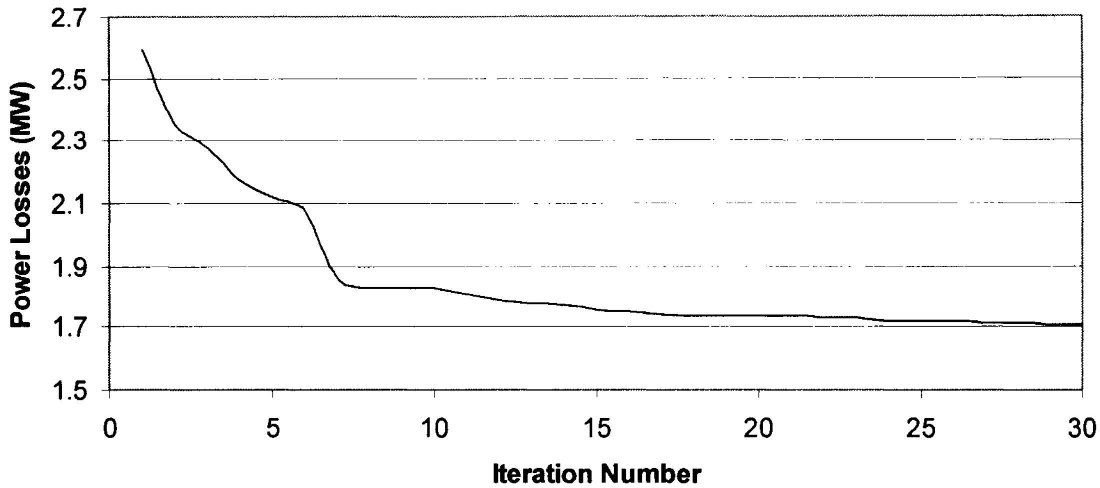

Figure 6.9. Convergence characteristic of the proposed approach in minimizing the real power losses.

<u>Case 3:</u> Since HPSO is capable of handling optimization problems in which the objective is not required to be convex or differentiable, the fuel cost function is augmented with an additional sine term as in Equation (6.7). This addition increases the degree of non-smoothness in the shape of the objective function significantly. Note that the fuel cost coefficients are modified to create more challenging objective function shape within the permissible operating range. The two coefficients e and f are made such that the generating units experience at least four ripples to give more realistic representation of real world power unit response [223]. The number of ripples is proportional to the degree of non-convexity in the shape of the objective function and it increases the difficulty of detecting the global solution. Figure 6.10 shows the shape of the fuel cost function of two generation units, which represents part of the overall problem, when the valve point effects are accounted for and in the absence of any constraints. Note that even when considering only two units, the shape of the objective is highly non-convex with multiple peaks and non-differentiable valleys. In this case, more particles are needed to explore this complex solution hyperspace efficiently. Table 6.4 tabulates the results obtained using different swarm's size. Increasing the swarm's size improved the HPSO performance in achieving better results at the expense of increased computational time.

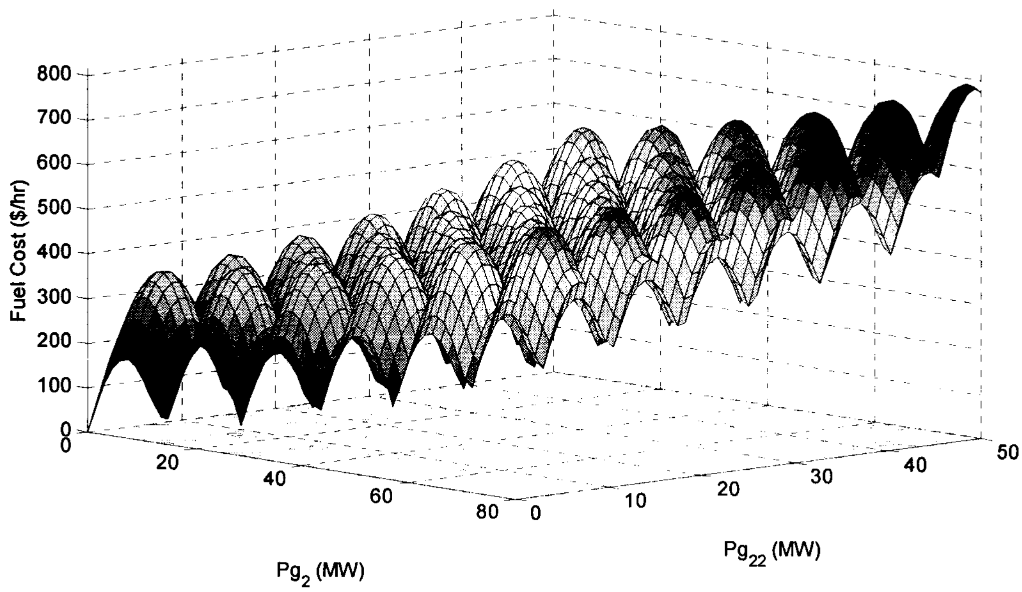

Figure 6.10. The high degree of non-convexity in the shape of the objective once valve loading effects are included.

To demonstrate the consistency and robustness of the developed algorithm, 20 independent runs were conducted for each case to measure the frequency of reaching the optimal or near optimal solution while maintaining the same stopping criteria (maximum iterations of 30). Results and computation time are shown in Table 6.5 that reflect the better performance of HPSO in solving the OPF problem.

It is evident that in Case 1, even the worst HPSO performance outperformed SQP in both fuel cost and emission minimization. However, it is noted here that in Case 3, there was a noticeable deviation between best and worst run when incorporating the valve loading effects into the fuel cost function. This is due to the highly non-smooth feasible region as a result of adding sine terms to the quadratic functions. Similar deviations were noted in earlier work conducted in [187;203] when considering the valve loading effects.

Table 6.4. Results of Case 3 Under Different Swarm Sizes

Swarm size	20	30	100
P_{g1}	47.068	47.095	47.126
P_{g2}	42.911	42.359	71.366
P_{g13}	8.790	35.902	8.972
P_{g22}	44.728	37.359	37.391
P_{g23}	8.983	8.826	8.993
P_{g27}	42.044	20.959	20.777
V_1	1.000	1.000	1.000
V_2	1.099	1.009	1.097
V_{13}	1.091	1.017	1.037
V_{22}	1.087	1.082	0.982
V_{23}	1.048	1.057	1.048
V_{27}	1.029	1.080	1.088
Q_{C5}	33.000	16.000	29.000
Q_{C24}	35.000	15.000	12.000
T_{6-9}	1.040	1.010	1.020
T_{6-10}	1.010	1.000	0.990
T_{4-12}	1.040	0.990	1.020
T_{27-28}	0.990	1.030	1.040
Objective	658.416	645.333	615.250

Table 6.5. Statistical Data for Cases 1-3

		Mean	Best	Worse	Standard Deviation	Average Time (s) /iteration
Case 1	Fuel Cost ($/hr)	575.704	575.411	576.339	0.263	5.974
	Emission (ton/hr)	283.110	282.628	283.874	0.386	6.172
Case 2	Fuel Cost ($/hr)	575.228	574.143	576.485	0.550	9.564
	Emission (ton/hr)	283.072	282.218	284.179	0.565	6.781
	P_{losses} (MW)	1.688	1.540	2.018	0.123	10.116
Case 3	20 Particles	744.306	658.416	849.511	61.224	8.519
	30 Particles	734.342	645.333	897.349	70.800	6.712
	100 Particles	677.222	615.250	753.868	42.461	22.870

Case 4: For better understanding of the effectiveness of the proposed hybrid inequality constraint treatments in enhancing the flying experience of the swarm in the search for an optimal solution, the algorithm was modified such that the SLA approach was incorporated to deal with the inequality constraints. Cases 2 and 3 were repeated with the same HPSO parameters previously used. The performance results of this version of PSO are tabulated in Table 6.6. This type of inequality constraints handling strategy degraded the PSO performance in solving the OPF in both cases and for all the objectives considered when compared to results shown in Table 6.5. As anticipated, multiple optimization variables (in some cases up to eight variables) were set to their limits. This signifies the importance of utilizing the memory element of each particle to recall its *pbest* position once it flies outside the feasible solution hyperspace.

Table 6.6. Statistical Data for Case 4

		Mean	Best	Worse	Standard Deviation
Case 2	Fuel Cost ($/hr)	577.511	575.389	581.813	1.718
	Emission (ton/hr)	289.321	283.445	302.355	5.116
	P_{losses} (MW)	1.873	1.573	2.145	0.197
Case 3	20 Particles	754.104	627.999	890.090	76.800
	30 Particles	748.652	620.047	879.785	70.860
	100 Particles	703.173	635.269	786.119	42.765

6.5 Summary

The work presented in this chapter investigates the applicability of HPSO in solving the OPF problem under different formulations and considering different objectives. The HPSO algorithm treats the OPF problem in three major steps: First, the optimal combinations of the mixed-type control variables are handled by the discrete HPSO to optimize convex and non-convex objectives. Secondly, the equality constraints, i.e. the power equations mismatch is minimized using the Newton-Raphson method in a separate subroutine. Thirdly, the inequality constraints are handled by the proposed hybrid constraints handling mechanism to preserve feasibility of solutions. Results are compared to the outcomes of other optimization techniques, namely SQP and modified PSO with conventional inequality constraints handling strategy. Comparison shows that HPSO consistently outperforms both techniques once its parameters are properly tuned. A study of HPSO parameters tuning is presented to enhance the optimizer performance in finding the minimum of several objectives. The PSO is combined with the Newton-Raphson algorithm to form a hybrid optimizer that can solve the discrete OPF problem including valve loading effects. This emphasizes the HPSO capability of handling optimization problems with greater complex modeling of system objectives and/or constraints. In contrast, most gradient-based optimization methods add more restrictions on the nature of the problem formulation like continuity, convexity, and differentiability to ensure finding the optimal solution. Sometimes, such restrictions may lead to intolerable modeling simplifications that can produce gross errors in computing the minimum of the objective at hand.

HPSO performance and robustness in its search for optimal solution is highly dependant on the tuning of parameters and the shape of the objective function. Objective functions with smooth shapes tend to require less particles and iterations to converge to the optimal solution while the ones with rough surface would require a greater number of particles and iterations to reach the same quality of solution.

Chapter 7

Conclusions and Recommendations

7.1 Conclusions

Improving the operational practices of electric power systems is desired at all times but the question remains in how can these goals be achieved. An optimal operational strategy is a multidimensional objective that can be interpreted in many ways. From a power company's point of view, it can be viewed as one of minimizing the overall system production cost so that the utility revenues are maximized. On the other hand, one can argue that it can be viewed from environmental perspectives as one of minimizing the overall harmful effects done on the environment as a result of generating electricity. These represent only two points of view, for the purpose of this thesis, but others still exist. Reaching an optimal stage of electric power system operations requires complex system modeling to handle different, and sometimes conflicting, aspects of such systems. More advanced analysis tools are required to cope with this rising complexity.

PSO is a relatively new optimization tool that has been adopted in this thesis to investigate its applicability to some optimization problems commonly encountered in power systems. Recently, added attention has been paid to exploiting the promising PSO potential in many different research fields. The research work involved in developing this thesis presents a step directed at attracting and adopting modern optimization tools to the area of electric power system analysis. The rapid interests of many researchers in this area can give a good indication to possibly expecting real world implementations of such tools in power systems analysis in the near future. They are mainly employed to alleviate some of the previously assumed modeling simplifications and to overcome some of shortcomings found in traditional optimization methods.

In this thesis, an attempt is made to try to fill some of the gaps that have been identified to further bridge PSO to the area of economic and environmental operations of power systems. The two main problems addressed in this work are the EED and the OPF. Even though, these two problems sometimes share the same objective functions, their formulations are quite different. The EED is formulated as a multi-objective optimization problem with continuous control variables and competing bi- and quad-objective functions. In the OPF formulation, both discrete and continuous control settings are used to reach the optimal operating strategy considering different objective functions, some of which are non-convex and non-differentiable. Modifications and improvements of the PSO are presented to improve its performance and to make it more suitable to some specific power system problems. The main improvements are made in handling constraints in a more efficient manner and in integrating other optimization tools with the PSO. Different approaches are proposed to solve the targeted problems and comparisons are made to evaluate these algorithms. The comparison is made against both traditional and evolutionary computation methods. Results reveal that one can have high expectations of the PSO potentials in the area of power system analysis.

7.2 Contributions

The research work involved in producing this thesis has led to several contributions that can be summarized as follows:

- It provides up-to-date literature reviews of the three main areas related to this work, i.e. PSO applications and developments in the area of power systems and recent work related to the EED and OPF problems. Each review is organized such that it can easily help researchers in power systems to identify and extend existing knowledge in order to plan for future research. The goals of these reviews are first to expand the reader's horizons to encompass what has been done and to identify what can be accomplished in these areas. Secondly, these are meant to provide good starting points for the newcomers who are interested in conducting scholarly research in any one of these areas.

- The EED problem is formulated as a constrained multi-objective optimization problem to properly incorporate both economic and environmental aspects of this problem. The problem formulations accounted for different models commonly used to represent the emissions of generating units. Then, a PSO algorithm is developed to solve the problem by aggregating the conflicting objectives into a scalar one via two different methods. The proposed approach eliminates the need to use augmented objective functions, thus, avoiding the necessity of properly selecting the penalty factors. The initialization process is carried out by steps that implement both random and deterministic rules to initialize the swarm. This process ensures satisfying the equality and inequality constraints throughout the search for an optimal solution.
- The proposed approach is used to capture the shape of the Pareto optimal set that shows the trade-off relationships between competing objectives. This curve gives the system operator additional information about the expected optimal value for a given objective with respect to other objectives.
- A hybrid tool is presented to solve the OPF problem in which HPSO searches for the most proper settings of the optimization variables, while the Newton-Raphson method is used to satisfy the highly nonlinear equality constraints. The hybrid algorithm incorporates a special operator to properly address the nature of the control variables since some of them are continuous while others are discrete. Different formulations of the OPF problems are proposed and solved considering different objectives that include one with non-differentiable and non-convex characteristics.
- The developed algorithms make use of the PSO memory elements to improve the efficiency of the search process. Results indicate that such utilization of each particle's memory can help significantly in improving the consistency and robustness of the optimizer's performance.

7.3 Recommendations for Future Work

The research work presented in this thesis can be further continued in many different directions. The following list highlights the most promising extensions to the research work presented in producing this thesis:

1. In the EED problem, the performance of PSO can be further analyzed in solving this problem with the presence of additional constraints such as prohibited zones, spinning reserve, and minimum up and down times for time varying loads. An interesting point would be to analyze the changes in the Pareto optimal set when accounting for these additional constraints.
2. A worthwhile study would be to formulate the EED problem with valve point loading effects and to investigate its impacts on the computed results.
3. Other aggregation methods such as goal programming and the ε-constraint method can be adopted to combine the EED conflicting objectives into a single scalar function. PSO performance can be then compared in solving the same problem with three different aggregation methods.
4. Discrete PSO algorithm can be developed to solve the unit commitment problem while accounting for environmental issues.
5. Dynamic weighting factors can be used to help in improving the uniformity of Pareto optimal set.
6. Fuzzy set theory can be used to model the uncertainty associated with the fuel cost and emission coefficients. Also, it can be used to represent the loading uncertainty. This will formulate the EED problem as fuzzy EED rather crisp EED.
7. Computation time of the OPF solution can be further reduced by implementing the HPSO algorithm in parallel processing units to execute the OPF faster. This can be done by dividing the swarm into segments and assigning each segment to a different processing unit to measure the fitness.
8. In the OPF problem, DC or other faster power solution methods may be implemented to reduce the execution time.

9. Additional constraints can be presented in the OPF formulation, such as reducing the impacts of the electromagnetic fields at certain segments of the transmission line network close to residential sites.
10. This study considered only one type of load modeling. Other more precise load modeling schemes can be investigated.

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Appendix A

Data for the Bi-Objective EED Simulation

1. Fuel cost and emission coefficients for IEEE 30-bus test system

Table A1. Fuel Cost Coefficients and Capacity Limits (30-bus)

Generator	a	b	c	Pmin(p.u.)	Pmax(p.u.)
1	10	200	100	0.05	0.50
2	10	150	120	0.05	0.60
3	20	180	40	0.05	1.00
4	10	100	60	0.05	1.20
5	20	180	40	0.05	1.00
6	10	150	100	0.05	0.60

Table A2. Emission Coefficients (30-bus)

Generator	α	β	γ	ζ	λ
1	0.04091	-0.05554	0.06490	0.000200	2.857
2	0.02543	-0.06047	0.05638	0.000500	3.333
3	0.04258	-0.05094	0.04586	0.000001	8.0
4	0.05326	-0.03550	0.03380	0.002000	2.0
5	0.04258	-0.05094	0.04586	0.000001	8.0
6	0.06131	-0.05555	0.05151	0.000010	6.667

2. Fuel cost and emission coefficients for IEEE 14-bus test system:

Table A3. Fuel Cost Coefficients and Capacity Limits (14-bus)

Generator	a	b	c	Pmin (MW)	Pmax (MW)
1	0.00156	7.92	561	100	250
2	0.00194	7.85	310	25	100
3	0.00482	7.97	78	10	50
4	0.00512	7.77	75	10	25
5	0.00509	7.54	77	5	10

Table A4. Emission Coefficients (14-bus)

Generator	α	β	γ
1	0.0126	-1.355	22.983
2	0.01375	-1.249	137.37
3	0.00765	-0.805	363.7
4	0.00693	-0.902	365.51
5	0.0045	-0.795	350.82

Appendix B

Data for the Quad-Objective EED Simulation

1. Fuel cost and emission coefficients for IEEE 30-bus test system

Table B1. Fuel Cost Coefficients and Capacity Limits

Generator	a	b	c	Pmin	Pmax
1	85.6348	8.43205	0.002035	150	400
2	303.7780	6.41031	0.003866	200	400
3	847.1484	7.42890	0.002182	350	600
4	274.2241	8.30154	0.001345	5	400
5	847.1484	7.42890	0.002182	270	500
6	202.0258	6.91559	0.005963	170	300

Table B2. NO_x Emission Coefficients

Generator	α	β	γ
1	80.9019	-0.38128	0.006323
2	28.8249	-0.79027	0.006483
3	324.1775	-1.36061	0.003174
4	610.2535	-2.39928	0.006732
5	324.1775	-1.36061	0.003174
6	50.3808	-0.39077	0.006181

Table B3. SO_x Emission Coefficients

Generator	α	β	γ
1	51.3778	5.05928	0.001206
2	182.2605	3.84624	0.002320
3	508.5207	4.45647	0.001284
4	165.3433	4.97641	0.110813
5	508.5207	4.45647	0.001284
6	121.2133	4.14938	0.003578

Table B4. CO_x Emission Coefficients

Generator	α	β	γ
1	5080.148	-61.01945	0.265110
2	3824.770	-29.95221	0.140053
3	1342.851	-9.552794	0.105929
4	1819.625	-12.73642	0.106409
5	1342.851	-9.552794	0.105929
6	11381.070	-121.9812	0.403144

Appendix C

Data for the 30-Bus Test System Used in the OPF Studies

Table C1. Characteristics of The Generating Units

Generator	1	2	3	4	5	6
a	0	0	0	0	0	0
b	2	1.75	1	3.25	3	3
c	0.02	0.0175	0.0625	0.00834	0.025	0.025
e	300	200	150	100	200	200
f	0.2	0.22	0.42	0.3	0.35	0.35
α	0.04091	0.02543	0.04258	0.05326	0.04258	0.06131
β	-0.05554	-0.06047	-0.05094	-0.03550	-0.05094	-0.05555
γ	0.06490	0.05638	0.04586	0.03380	0.04586	0.05151
Pmin(MW)	0	0	0	0	0	0
Pmax(MW)	80	80	50	55	30	40
Qmin(Mvar)	-20	-20	-15	-15	-10	-15
Qmax(Mvar)	150	60	62.5	48.7	40	44.7
Bus Number	1	2	22	27	23	13

Table C2. Bus Data for IEEE 30-Bus System

Bus No.	Pd	Qd	Qc	V_{min}	V_{max}
1	0	0	0	0.95	1.1
2	21.7	12.7	0	0.95	1.1
3	2.4	1.2	0	0.90	1.05
4	7.6	1.6	0	0.90	1.05
5	0	0	19	0.90	1.05
6	0	0	0	0.90	1.05
7	22.8	10.9	0	0.90	1.05
8	30	30	0	0.90	1.05
9	0	0	0	0.90	1.05
10	5.8	2	0	0.90	1.05
11	0	0	0	0.90	1.05
12	11.2	7.5	0	0.90	1.05
13	0	0	0	0.95	1.1
14	6.2	1.6	0	0.90	1.05
15	8.2	2.5	0	0.90	1.05
16	3.5	1.8	0	0.90	1.05
17	9	5.8	0	0.90	1.05
18	3.2	0.9	0	0.90	1.05
19	9.5	3.4	0	0.90	1.05
20	2.2	0.7	0	0.90	1.05
21	17.5	11.2	0	0.90	1.05
22	0	0	0	0.95	1.1
23	3.2	1.6	0	0.95	1.1
24	8.7	6.7	4	0.90	1.05
25	0	0	0	0.90	1.05
26	3.5	2.3	0	0.90	1.05
27	0	0	0	0.95	1.1
28	0	0	0	0.90	1.05
29	2.4	0.9	0	0.90	1.05
30	10.6	1.9	0	0.90	1.05

Table C3. Branch Data for IEEE 30-Bus System

From	To	R	X	B
1	2	0.02	0.06	0.03
1	3	0.05	0.19	0.02
2	4	0.06	0.17	0.02
3	4	0.01	0.04	0
2	5	0.05	0.2	0.02
2	6	0.06	0.18	0.02
4	6	0.01	0.04	0
5	7	0.05	0.12	0.01
6	7	0.03	0.08	0.01
6	8	0.01	0.04	0
6	9	0	0.21	0
6	10	0	0.56	0
9	11	0	0.21	0
9	10	0	0.11	0
4	12	0	0.26	0
12	13	0	0.14	0
12	14	0.12	0.26	0
12	15	0.07	0.13	0
12	16	0.09	0.2	0
14	15	0.22	0.2	0
16	17	0.08	0.19	0

Table C3. Branch Data for IEEE 30-Bus System

From	To	R	X	B
15	18	0.11	0.22	0
18	19	0.06	0.13	0
19	20	0.03	0.07	0
10	20	0.09	0.21	0
10	17	0.03	0.08	0
10	21	0.03	0.07	0
10	22	0.07	0.15	0
21	22	0.01	0.02	0
15	23	0.1	0.2	0
22	24	0.12	0.18	0
23	24	0.13	0.27	0
24	25	0.19	0.33	0
25	26	0.25	0.38	0
25	27	0.11	0.21	0
28	27	0	0.4	0
27	29	0.22	0.42	0
27	30	0.32	0.6	0
29	30	0.24	0.45	0
8	28	0.06	0.2	0.02
6	28	0.02	0.06	0.01