Economic and Economic-Emission Operation of All-Thermal and Hydro-Thermal Power Generation Systems Using Bacterial Foraging Optimization

by

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To my parents and all of my family who offered me unconditional love and support throughout the course of this thesis.

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ABSTRACT

Electric power is a basic requirement for present day life and its various economic sectors. To satisfy the ever-increasing needs for electricity, the number of generating units, transmission lines and distribution systems is rising steadily. In addition, electric power systems are among the most complex industrial systems of the modern age. Beside complexity, the generation of electric power is a main source of gaseous emissions and pollutants. The planning and operation of electric power systems must be done in a way that the load demand is met reliably, cost-effectively and in an environmentally responsible manner. Practitioners strive to achieve these goals for successful planning and operations utilizing various optimization tools. It is clear that the objectives to be satisfied are mostly conflicting. In particular, minimizing the fuel cost and the gaseous emissions are two conflicting and non-commensurate objectives. Therefore, multi-objective optimization techniques are employed to obtain trade-off relationships between these incompatible objective functions in order to help decision makers take proper decisions.

In this thesis, two main power system operation problems are addressed. These are the economic load dispatch (ED) and the short-term hydro-thermal generation scheduling (STHTS). They are treated first as single-objective optimization problems then they are tackled as multi-objective ones considering the environmental aspects. These problems, single and multi-objective, are nonlinear non-convex constrained optimization problems with high-dimensional search spaces. This makes them a real challenge for any optimization technique. To obtain the optimal or close to optimal solutions, a modified bacterial foraging algorithm is proposed, developed and successfully applied. The bacterial foraging algorithm is a metaheuristic non-calculus-based optimization technique. The proposed algorithm is validated using diverse benchmark optimization examples before implementing it to solve the problems of this thesis. Various practical constraints are considered in the different cases of each problem. These include transmission losses, valve-point effects for both the ED and the STHTS problems and water availability and reservoir configurations for the STHTS problem. In all cases the optimal or near-optimal solution is obtained. For the multi-objective optimization cases, the Pareto optimal solution set that shows the trade-off relationship between the conflicting objectives is successfully captured.

LIST OF ABBREVIATIONS AND SYMBOLS USED

List of Abbreviations

STHTS	Short-Term Hydro-Thermal Scheduling
ED	Economic Dispatch
B&B	Branch and Bound
GA	Genetic Algorithms
EP	Evolutionary Programming
SA	Simulated Annealing
PSO	Particle Swarm Optimization
DE	Differential Evolution
IP	Interior Point
BFA	Bacterial Foraging Algorithm
MBFA	Modified Bacterial Foraging Algorithm
LP	Linear Programming
NLP	Nonlinear Programming
SQP	Sequential Quadratic Programming
GRG	Generalized Reduced Gradient
E. coli	*Escherichia coli*
ED	Economic Dispatch
LIM	Lambda Iteration Method
PS	Pattern Search
SWT-NR	Surrogate Worth Trade-off with Newton-Raphson
LGIM	Lambda-Gamma Iteration Method
GS	Gradient Search
IFEP	Improved Fast Evolutionary Programming

List of Symbols

$F(x), f(x)$	Objective Function
x	Vector of Variables or Unknowns
$g(x)$	Vector of Equality Constraints
$h(x)$	Vector of Inequality Constraints
∇	Gradient
θ	Position of a Bacterium in the Search Space
$J(\theta)$	Nutrient function for the bacterium at θ
S	Size of Bacteria Population
$P(j,k,l)$	Position of a Bacterium at Steps j , k and l
N_C	Maximum Number of Chemotactic Steps
$C(i),C(i,j)$	Chemotactic Step Size (Run-Length Unit) for the i^{th} Bacterium
$\phi(j)$	Random Direction Unit for the j^{th} Chemotactic Step
N_S	Maximum Number of Swimming Steps in the Same Direction
J_{CC}	Cell-to-Cell Signaling Function
$d_{attract}$	Depth of Bacterial Attractant Signal
$w_{attract}$	Width of Bacterial Attractant Signal
$h_{repellent}$	Height of Bacterial Repellent Signal
$w_{repellent}$	Width of Bacterial Repellent Signal
N_{re}	Maximum Number Reproduction Steps
S_r	Number of the Healthiest Half of Bacteria
N_{ed}	Maximum Number of Elimination/ Dispersal Events
p_{ed}	Probability of Elimination/ Dispersal Event for each Bacterium
$\Delta(i)$	Random Vector Generated for the i^{th} Bacterium’s Tumble
F_{eval}	Evaluation Function
A,y,z	Constant Parameters for Penalty Functions
a_i,b_i,c_i,e_i,f_i	Fuel Cost Function Coefficients

$F(P_{gi})$	Cost Objective Function for Thermal Unit i
P_{gi}	Active Power Generation for Thermal Generating Unit i
P_D	Total Load Demand
N_g	Number of Thermal Generating Units
M_H	Number of Hydro Generating Units
$P_{gi}^{\min}$	Minimum Power Generation for Thermal Generating Unit i
$P_{gi}^{\max}$	Maximum Power Generation for Thermal Generating Unit i
$P_{Hj}^{\min}$	Minimum Power Generation for Hydro Generating Unit j
$P_{Hj}^{\max}$	Maximum Power Generation for Hydro Generating Unit j
F_T	Total Fuel Cost Function
P_L	Active Transmission Power Losses
$B_{ij}, i, j = 0,1,...N_g$	Loss Formula Coefficients
P_H	Output Active Hydro Power Generation
P_{Hj}	Active Power Generation for Hydro Generating Unit j
q	Rate of Water Discharge
h	Effective Water Head
η_t	Turbine Efficiency
η_G	Generator Efficiency
A	Area of the Reservoir
h_0	Minimum Water Head
T	Scheduling Time Period
N_k	Number Scheduling Time Intervals
n_k	Number of Hours in Scheduling Time Interval k
$F_m(P_{gi})$	Cost or Emission m^{th} Objective Function for Thermal Unit i
NO_x	Nitrogen Oxides
SO_2	Sulphur Dioxide
CO_2	Carbon Dioxide

d_{1i}, e_{1i}, f_{1i}	NO_x Emission Function Coefficients
d_{2i}, e_{2i}, f_{2i}	SO_2 Emission Function Coefficients
d_{3i}, e_{3i}, f_{3i}	CO_2 Emission Function Coefficients
M	Number of Objective Functions
w_k	Weighting Factor for Objective k

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CHAPTER 1 INTRODUCTION

1.1 MOTIVATION

Electric power systems are among the most complex industrial systems of today's civilization that play a central role in the functioning of modern societies. In order to perform this role, production and delivery of electric power must be achieved reliably, cost-effectively and in an environmentally responsible approach. Successful planning and operation of electric power generation, transmission and distribution is a continual challenge to electric power engineers all over the world. A prime objective in the operation and planning mission is to meet the power load demand at the lowest possible cost. A more imperative objective is the safety of individuals and equipment. Reliability and continuity of service are among the various essential planning and operational considerations. In addition to these objectives, minimizing the environmental impact of power generation is getting to be exceedingly important as a consequence of the increase in the number of power plants.

Electric power is mostly produced from conventional non-renewable energy sources such as oil, natural gas and coal in addition to nuclear and hydro sources. Thermal plants that burn fossil fuels generate the major share of worldwide electric energy. In such plants heat energy is released and converted to mechanical form of energy which consequently generates electricity. This energy conversion is processed through thermal cycles with conversion efficiencies less than 40% [1]. Clearly this increases the fuel consumption and decreases the existing resources. Furthermore, the continuous increase in the global demand on electric energy is accelerating the depletion of the limited and irreplaceable fuel supplies.

Achieving the efficient and optimal economic load dispatch is one of the important tasks in power system operations. This is the optimum allocation of the load among various committed plants in such a way that production cost is minimized. The static optimization problem of classic economic dispatch deals with the scheduling of all-thermal generation units that are pre-selected by a unit commitment program [2].

The hydro-thermal generation scheduling is another operational optimization problem that has attracted increasing attention. This dynamic optimization problem is different from the all-thermal case as it deals with both thermal and hydro plants. It determines the optimal scheduling of thermal and hydro generation over a period of time to meet the load demand at the minimum production cost of the thermal generating units. This involves using up the available water resources to maximize the hydro-electric generation and hence minimize the fuel cost associated with the thermal generation. In addition to power generation considerations, various hydraulic obligations must be met. These include, for instance, maximum forebay elevation, reservoir discharge rate and spillage and other hydraulic constraints. Besides, other characteristics of hydro-electric plants such as their location, number of units, configuration of these units and special operating features are to be considered [3].

The issue of environmental impacts and air pollution associated with power generation has become another important consideration of today's power system operational practice. A significant portion of the total air pollutants and gaseous emissions in the atomosphere is produced from burning fossil-based fuels in power plants. The harmful effects of the various pollutants, such as nitrogen oxides NO_x, sulphur dioxide SO_2 and carbon dioxide CO_2, are attracting great public concern so that they cannot be removed from any operational and planning strategy. In order to minimize these impacts on human life and the atmosphere at large, strict environmental laws and firm restrictions have been internationally imposed on power generation industry. The Clean Air Amendment of 1990, for instance, is one of these environmental laws that aim to control and minimize gaseous emission [4-8].

In light of this situation, optimizing power system operations can no longer be achieved by only minimizing fuel costs but also strive to reduce various gaseous emissions as well. To handle these conflicting objectives, various multi-objective optimization techniques have been proposed and applied to solve the economic-emission optimal power system operations. Emission minimization has extensively become associated to both economic load dispatch and hydro-thermal generation scheduling problems. As a result of solving these multi-objective optimization problems, the decision maker is provided with the tools to take the proper decision regarding the trade-off between the conflicting objectives of cost and emissions.

The above mentioned operational power system tasks are nonlinear large-scale constrained optimization problems with single or multiple objective functions. There are various optimization techniques that have been proposed and applied to resolve these problems. Traditionally, the majority of these optimization methods are deterministic and derivative-based techniques while most of the recently proposed methods are heuristic in nature. Heuristic methods, which are in most cases inspired by the various biological and natural phenomena, have been attracting more and more attention due to many reasons such as simplicity, flexibility and generality. It is obvious that in either case of deterministic or heuristic methods, using digital computers is the only realistic tool to tackle such large-scale nonlinear optimization problems of power system operations.

1.2 Thesis Objectives and Contributions

Optimal economic and economic-emission operations of power generation systems are comprehensively investigated in this thesis considering various operational obligations. The conventional optimal economic dispatch and optimal short-term hydro-thermal generation scheduling problems are studied thoroughly taking into account various realistic constraints. Including the environmental aspects in the formulation and implementation of the above mentioned problems is considered next.

A major goal of this thesis is to develop and implement the bacterial foraging algorithm (BFA) to solve the above stated power system problems. In this regard, the aim is to attempt to enhance the BFA and modify it extensively to tackle the nonlinear large-scale optimization problems considered in this thesis. The basic BFA was not originally designed to handle constrained problems and hence it is important to set up an appropriate constraint-handling mechanism and incorporate it in the algorithm. Furthermore, concerning some of the drawbacks associated with the basic BFA, such as its poor performance with high-dimensioned problems, it is an important goal of this work to come up with an adaptive and effective solution approach. In order to treat the shortcomings of the BFA and to develop it to effectively fit these problems; it is a key objective to put forward a modified version of the BFA.

A main objective of this work is to study, formulate and solve the conventional economic dispatch problem using the proposed algorithm. Main practical operational constraints such as transmission power losses and valve-point effects are also considered in the formulation of this problem. In this regard, the proposed algorithm is validated by solving this basic power system optimization problem and comparing the results to those obtained by other optimization techniques.

The basic focus of the research conducted in this thesis is the optimization problem of short-term hydro-thermal generation scheduling. The aim here is to present a comprehensive discussion on the problem statement, formulation and implementation in compliance with the scope of this thesis. With respect to the wide range of operational and hydraulic obligations associated with the problem, it is important to take into consideration the various realistic constraints of the problem. The complexity of this large-scale problem makes it a challenge to all optimization methods, therefore it is essential to validate the proposed algorithm by working out as many different case studies as possible. In this regard, in addition to electrical constraints, a fundamental intention is to consider systems of hydraulically coupled and uncoupled plants with fixed and variable-head reservoirs as well as cascaded chain systems.

The last but not least important objective is the inclusion of the environmental aspects in the formulation of the above mentioned problems. This is to formulate these two problems as multi-objective optimization problems with multiple conflicting objectives. In particular, the economic-emission dispatch problem is formulated to minimize fuel cost and gaseous emissions simultaneously. Afterwards, the multi-objective optimization problem of the short-term hydro-thermal scheduling is formulated to consider minimizing emissions all together with fuel cost while obtaining the optimal scheduling.

In order to accomplish the objectives targeted by this effort, a number of contributions have been made in this thesis. These are attempts to add to the literature of economic power system optimization and development of heuristic optimization techniques. One of the major contributions is presenting the state of the art of the main subjects discussed in the thesis. In this regard, a detailed literature survey on the recent developments in the fields of power system optimization is provided.

Another important contribution is proposing an improved and enhanced heuristic bacterial foraging algorithm by modifying the basic BFA. The modified bacterial foraging algorithm (MBFA) is developed to have dynamic and adaptive features so that it has become capable of tackling nonlinear large-scale optimization problems with high dimension search spaces. In particular, the chemotactic step (or the run-length unit), which is the basic element for updating the solution vector in the BFA, is modified to have dynamic and adaptive characteristics. Furthermore, the stopping criterion of the basic BFA is also adjusted by proposing a more effective course of action for stopping the search operation. These modifications have led to better performance in terms of execution time and balancing the exploration and exploitation of the search.

With the purpose of dealing with the constrained optimization problems studied in the thesis, an effective equality constraint-handling mechanism is proposed for the BFA. This is a dynamic scheme that adjusts the penalty factor according to the improvement of the objective function and the iterations of the algorithm. In addition, inequality constraint-handling technique is developed for the BFA to maintain the feasibility of the solution. In this regard, the proposed technique guarantees the preservation of the feasible solutions and the rejection of the infeasible ones at the same time.

Developing and implementing the MBFA to solve the problems discussed in this thesis without requiring adjusting any of its features is another contribution. In addition, the same algorithm is employed to capture the Pareto optimal set of solutions for the multi-objective optimization problems in this work. It should be mentioned that the ability of the proposed algorithm to obtain the trade-off curves can be generalized for other multi-objective optimization problems.

1.3 Thesis Outline

This thesis is divided into two parts and organized in seven chapters. The first part, which includes the first three chapters, is devoted to providing the background preparation and tools necessary for problem definition, modeling and implementation. The second part is dedicated to problem statement, formulation, solution and discussion.

The motivation behind this research as well as thesis objectives and contributions are introduced in this first chapter. In addition, a brief description of the scope of the thesis is given in this chapter. In the second chapter a detailed literature review is presented covering the research areas of the thesis. The third chapter presents briefly the basic concepts of the optimization theory that are needed for the dissertation. Solution methodologies for both single and multi-objective optimization problems are also summarized in the chapter. In addition, the basic Bacterial Foraging Algorithm (BFA) is presented and discussed. The Modified Bacterial Foraging Algorithm (MBFA), which is developed and applied in this thesis, is also presented in Chapter 3 along with the developed constraint-handling methods that are utilized in the thesis. The fourth chapter addresses the classical economic dispatch problem of all-thermal generation considering transmission losses and valve-point effects. The short-term hydro-thermal generation scheduling problem is the subject of the fifth chapter considering fixed-head and variable-head hydro plants. Both hydraulically isolated and hydraulically coupled plants are studied and discussed. The sixth chapter is devoted to the economic-emission load dispatch of power generation as a multi-objective optimization problem considering the environmental aspects. Here both the all-thermal and hydro-thermal generation scheduling problems are dealt with considering the minimization of not only the cost but also the gaseous emissions. The last chapter provides the conclusions, remarks and some ideas and hints for future work related to the scope of this thesis.

CHAPTER 2 LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, a comprehensive survey of the areas of the research conducted in this thesis is presented. Based on the research area of interest, this review covers the recently published work related to power generation optimal scheduling. To provide the necessary background of the thesis subject, this review is divided into two main parts. The first part offers an up to date survey and discussion on the optimization methods used to solve the short-term hydro-thermal generation scheduling problem. The second part covers recent published papers on the field of multi-objective economic-emission dispatch and generation scheduling where the environmental aspects are considered. In the two parts, a review and a methodology-based classification of most of the publications on these topics are presented.

2.2 OPTIMIZATION METHODS FOR SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING

Short-term hydro-thermal scheduling (STHTS) consists of determining the optimal usage of available hydro and thermal resources during a scheduling period of time (1 day to 1 week) [2, 3]. This is to determine, optimally, which of the thermal generating units should run as well as the power generated by the hydro and thermal plants so that the total cost is minimized. Minimizing the total cost in this optimization problem is subject to many control and operational constraints. In addition to reliability and security requirements, hydraulic and thermal constraints may include load balance, generation limits, water discharge, starting and ending storage volume of water and spillage discharge rate. Furthermore, in order to solve the hydro-thermal scheduling problem, thermal unit commitment and economic load dispatch problems should be solved all together with the hydro schedules. Therefore, the STHTS is a large-scale nonlinear and complex constrained power system optimization problem.

A variety of optimization methods and techniques have been proposed to solve the problems of power systems optimal operations and planning since the beginning of the last century [3]. Among the earliest optimization techniques applied to the problem were the so-called “base load procedure”, “the best point loading” and the “incremental method”. A historical survey, which highlights the earliest works in the field, is offered in [3]. At present, several methods and algorithms have been in use to solve power system optimization problems [9, 10]. These include variational methods, iterative approaches, artificial intelligence tools, and hybrid techniques. Over the years, different methodologies have been applied. With the development of the mathematical and computational techniques, additional details of the problem formulation have been addressed. In the beginning, only thermal plants were considered and before long, the hydraulic operational and topological constraints were treated. Figure 2.1 statistically illustrates the number of the published research papers on the subject of the STHTS problem during the last 20 years (based on IEEE/IET/Elsevier databases).

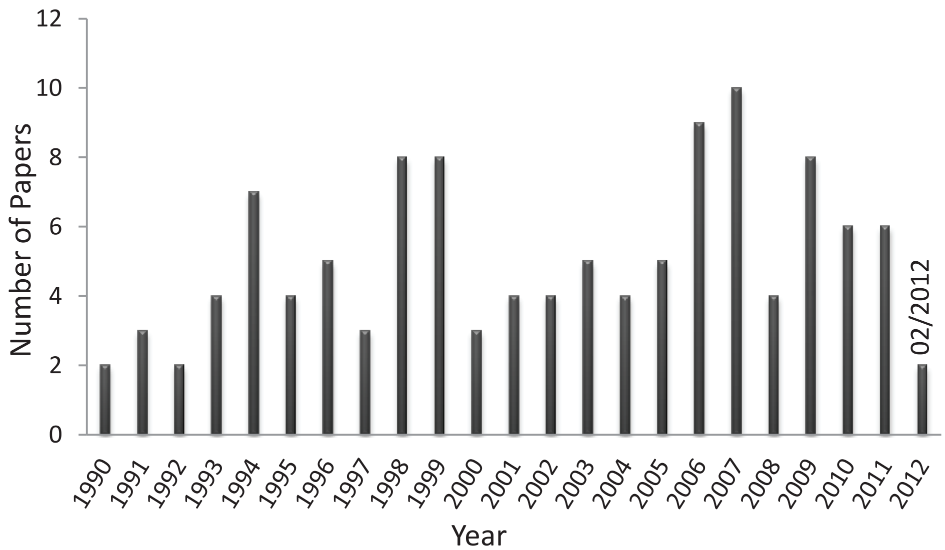

Figure 2.1 Papers published in each year on the subject of STHTS problem.

A wide range of optimization techniques has been applied to solve the STHTS problem. These techniques are principally based on the criterion of local search through the feasible region of solution [9]. Applied optimization methods can be mathematical programming algorithms such as linear and nonlinear programming, dynamic programming and interior point methods [11, 12]. Among the other methods are the artificial intelligence techniques including neural networks, fuzzy systems and the evolutionary methods such as genetic algorithms and simulated annealing. The methods considered in this survey can be classified as follows:

- Lagrangian relaxation and Benders decomposition-based methods
- Interior point methods
- Mixed Integer programming
- Dynamic programming
- Evolutionary computing methods
- Artificial intelligence methods
- Optimal control methods

These optimization methods can be generally classified into two main groups: deterministic methods and heuristic methods. Deterministic methods include Lagrangian relaxation and Benders decomposition methods, mixed integer programming, dynamic programming and interior point methods. Genetic algorithms, particle swarm optimization and other evolutionary methods are heuristic. Most of the methods that have been used to solve the STHTS problem are deterministic in nature. However, modern heuristic methods are getting more attention in solving large-scale optimization problems. To search for the optimal solution, classical deterministic methods, also known as derivative-based optimization methods, apply techniques such as the gradient and Hessian operators. They use single path search methods while heuristic methods use population-based search techniques to search the solution hyperspace. This difference, in fact, is an advantage for the heuristic methods as it helps searching in spaces with non-smooth characteristics. It also improves convergence for heuristic methods and makes it less dependent on the initial solution points. Being derivative-free, modern methods are applicable to any optimization problem regardless of the linearity or nonlinearity of its objective function and constraints. In contrast, different deterministic methods are required for different optimization problems. Another main difference between the two classes is that heuristic methods use stochastic techniques and include randomness in moving from one solution to the next while determinist methods follow deterministic transition rules. This, of course, gives an advantage to heuristic methods in avoiding local minima. In spite of the advantages of heuristic techniques, classical methods have been used by the majority of research papers covered in this review. The reason is their efficiency in solving optimization problems, the solid mathematical foundation and the availability of software tools [13].

Figure 2.2 shows the number of publications and the methods applied to solve the STHTS problem in the specified period. In this survey, most of the papers that have been published during the past two decades or so are included (based on IEEE/IET/Elsevier databases).

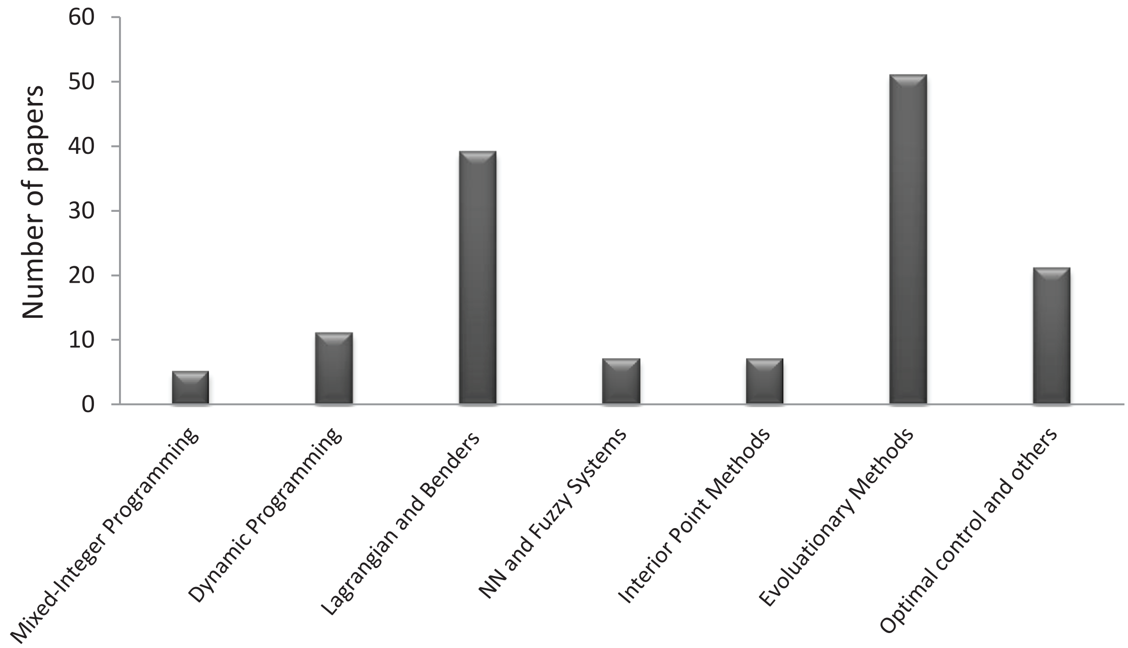

Figure 2.2 Number of papers published on different optimization methods used.

2.2.1 Lagrangian Relaxation and Benders Decomposition Methods

Large-scale optimization problems, such as the STHTS problem, are usually divided into a set of independent sub-problems. Decomposition-based methods are used to solve this kind of problem using an iterative-based methodology. Lagrangian relaxation and augmented Lagrangian techniques are among the most popular decomposition based methods. The original Lagrangian relaxation technique was improved by introducing the augmented Lagrangian and the multiplier updating methods. In these techniques, the solution is based on computing the optimal values of the Lagrangian multipliers for the sub-problems to find a solution to the dual problem. On the other hand, the solution to the primal problem is usually infeasible due to the non-convexity of the problem. Therefore, a method to find a feasible optimal or near-optimal solution has to be applied. Lagrangian multipliers are updated each iteration using several updating tools such as Bundle techniques. Benders decomposition and Dantzig-Wolfe are also well-known decomposition methods [9]. A study of the relaxed classical hydro-thermal scheduling algorithm from a theoretical point of view was presented in [14, 15]. The focus of these papers was the convergence issues of the Lagrangian formulation of the hydro-thermal scheduling problem. A relaxation coefficient was proposed to improve the algorithm's convergence prospects and practical procedures to compute the coefficient were presented. To illustrate the performance of the algorithm in [15], it was implemented on a real system although many details were neglected in the formulation of the problem. This was because, as mentioned, the scheduling problem itself was not the subject of this paper.

A method based on Lagrangian relaxation was also presented by Yan *et al.* in [16] where the STHTS problem was decomposed into two sub-problems. A method of merit order allocation was implemented to solve the hydro sub-problem while the thermal sub-problem was solved by applying a dynamic programming approach. The method was tested using limited water resources hydro units. The hydraulic coupling among these water resources and the upper and lower constraints were not considered. The hydro sub-problem was formulated as a linear programming problem without accounting for the nonlinear characteristics. The nonlinearity that could be caused by the start up cost function for the thermal units was not taken into consideration. Power exchange with other utilities was also not included in this paper. The authors did not consider the pumped storage power units in this paper but in a subsequent paper [17]. They presented a method to incorporate them where a solution methodology for pumped storage units was also presented. The dynamic transition regarding the operation status (generation, pumping and idle) of the pumped storage units was considered by the Lagrangian relaxation based solution. The algorithm was integrated with a scheduling package and implemented to solve the STHTS problem where the importance of the pumped storage units was demonstrated. It should be noted that the pumped storage unit implemented was always running as either a generator or a pump with short off time. The convergence of the algorithm was reported to be very good although a few additional iterations were required for updating the Lagrangian multiplier using a sub-gradient approach.

A peak-shaving method was presented in [18] to study the influence of the interchange resource scheduling on the STHTS problem. The interchange was formulated as a decomposed sub-problem with a proposed scheduling strategy to provide a smoother hydro generation profile. The methodology was claimed to be suitable for practical systems although it was only applied to two test synthetic systems. Results showed that the method was beneficial especially for the systems that could be augmented by interchange purchases. In [19], a network flow programming based algorithm was presented to solve the STHTS problem of dominantly hydro systems. The hydraulic subsystem was simulated while the transmission system was modeled as an optimal DC load flow. The performance of the approach was found to be efficient when applied to two synthetic test systems. The tests were performed using amateur codes that made the time of convergence an issue of a concern. Network flow programming was applied to solve the hydro sub-problem in a number of papers such as [20]. This paper presented an implementation of an incremental network flow programming and integrated it with an existing unit commitment and economic dispatching software. The objective was to develop a comprehensive industrial hydro-thermal scheduling product for applications in an energy management system. The approach was implemented in a realistic system and showed acceptable performance with good convergence properties in spite of employing a modified golden search algorithm. It might be worth mentioning that the golden search could get trapped in local minima due to nonlinearity of the problems considered. However, the authors reported that, fortunately, their algorithm gave very satisfactory results.

In [21], a network flow programming algorithm was applied to a hydro dominated power system. The problem was decomposed into hydro and electric sub-problems. Constraints were represented in detail by network models including transmission DC power flow model. The approach was tested using a practical system; however, convergence required extended time. The hydro-thermal scheduling problem in a hydro dominated power system was the subject of [22]. In this paper, a case study was presented considering that the solution of the unit commitment problem was predetermined and, hence, thermal start up and shut down operations and power rate restrictions were not considered. On the other hand, many constraints were formulated such as reservoir release targets, power flow transmission limits, reservoir storage limits and discharge variation limits.

Augmented Lagrangian relaxation is also another decomposition-based method that was presented in a number of papers such as [23]. In this paper, the augmented Lagrangian decomposition and coordination technique was applied to the STHTS problem instead of the standard Lagrangian relaxation approach. Reducing the oscillation of the solutions to the sub-problems in the standard Lagrangian relaxation technique was an objective of the augmented Lagrangian approach. By applying this method, the linearity and piecewise linearity of the cost functions of the sub-problems were avoided and hence the oscillations were reduced. Compared to the standard Lagrangian relaxation, the augmented Lagrangian approach requires less computational time with better convergence characteristics although oscillations were not eliminated. This lead to a smooth movement of the solutions to the sub-problems with a slight change of the value of multipliers. The approach was tested using a practical system consisting of thermal, hydro and pumped storage units with many practical constraints were considered. It should be pointed out that the selection of the penalty coefficient was not easy, as it could be not appropriate for all different units. The oscillations of the solutions to the sub-problems in the Lagrangian relaxation technique as well as the singularity of these solutions were also discussed in [24]. In this paper, a nonlinear approximation method was presented. Quadratic nonlinear functions were used to approximate linear cost functions. The algorithm was tested and applied to a practical system and the results demonstrated its efficiency although when compared to the standard Lagrangian relaxation method, no difference in the computational time was reported.

In [25, 26] a Lagrangian relaxation-based algorithm and a dynamic programming technique were integrated into an expert system to solve the STHTS problem. Steam and gas turbines were considered as well as many constraints such as the nonlinearity of thermal generation cost, transmission losses and the water discharge rates. The algorithm was reported to reach a feasible solution in an acceptable time although additional iterations were required in some test cases to find the optimal Lagrangian multipliers for the nearest feasible solution. Guan *et al.* presented a Lagrangian relaxation-based technique for the STHTS problem in [27]. They concentrated on the solution methodology for the hydro sub-problem with the cascaded reservoirs and discrete hydro constraints. In the formulation of the problem, the hydro units were represented by one equivalent unit and only one existing river catchment was assumed. Ramp rates and system losses constraints were not included in the formulation. The algorithm was tested using a realistic system and a near-optimal solution was confirmed. The computational time was assumed good although the results were not compared to those of other approaches.

Updating the Lagrangian multipliers was addressed by several papers to overcome the problems associated with the commonly used sub-gradient updating method. In [28], an application of a bundle method called "the Bundle Trust Region Method" was presented and applied to update the Lagrangian multipliers. The categorization of the presented method as a trust region method was a point of debate since a method could be defined as a trust region method if a dynamic modification is applied to the feasibility region whilst this approach could be better classified as a dual penalty cutting plane method. The method was compared to the sub-gradient method and other bundling methods and found to have faster convergence although only the line search rule was used to compute the ascent direction.

An alternative bundling method to update the multipliers was presented in [29]. This algorithm was called "reduced complexity bundle method" and used to obtain better convergence and to avoid the zigzagging behavior of the conventional bundle method, which could cause a slow convergence. Tests were run using practical data sets with various realistic considerations included. Results showed better feasible solutions to the dual cost function compared to the sub-gradient method although no guarantee of convergence was offered. It should be mentioned that some details in the methodology were not made clear such as the procedure of selecting the bundle elements and how they were projected.

Dual programming algorithms were applied to solve the thermal generation scheduling sub-problem as part of the STHTS problem in [30]. Two methods were implemented and tested using both small and large-scale test systems. Results were considered to have good convergence characteristics. In [31], an updating technique for the Lagrangian multipliers was presented. This technique was called the optimal distance method. The method was tested and compared to the sub-gradient method and proved to have better convergence properties and accuracy of solution. However, convergence in some test cases was not reached easily and more iterations were required to find a feasible solution. Another updating approach for the Lagrangian relaxation multipliers was presented in [32]. This approach was referred to as “a novel, non-oscillating and efficient multiplier updating procedure”. The procedure was tested and showed superiority when compared to the sub-gradient and bundling methods based on the number of iterations required.

Reference [33] presented a novel relaxation algorithm to solve river catchment sub-problems taking into consideration the continuous and discontinuous dynamics and constraints as well as hydraulic coupling of cascaded reservoirs. In this approach, another set of multipliers was used to relax the minimum hydro generation of each hydro unit. The algorithm considered the pumped storage units in addition to thermal and hydro units, which were represented by one unit. A near-optimal feasible solution was obtained when the algorithm was tested. However, there were some concerns regarding convergence issues when compared to a previously applied heuristic method. Bidding in energy markets and its influence on the hydro-thermal problem was the subject of [34]. The paper presented a novel formulation to integrate bidding and hydro-thermal scheduling based on a Lagrangian relaxation approach. A Markov chain model was employed to present the hourly market cleaning prices considering the reserve market and the self-scheduling requirements. The problem was decomposed into a number of sub-problems that were solved using a stochastic dynamic programming approach. Pumped storage hydro units were also included and many practical considerations were formulated although, for simplicity, some assumptions regarding the market clearing prices and the “perfect market” were applied.

In [35], an augmented Lagrangian method was used to solve the STHTS problem considering the transmission constraints and including pumped storage units in the model. The method was tested using the IEEE 24-bus system and the results showed that a feasible solution was reached with no more iterations required for the economic dispatch algorithms. The method was reported to be accurate and practical though it was not applied to realistic systems. With respect to convergence properties, it was suggested that the augmented Lagrangian approach could be improved by using suitable updating methods. In [36, 37], various techniques were applied to relax the Lagrangian relaxation multipliers. These are; Datzig-Wolfe linear programming, sub-gradient method and Branch & Bound. Real generation data was used to perform the application of the methods considering many practical constraints such as system losses and other thermal and hydro limits but not the ramp rates. Results were shown to demonstrate the effectiveness and optimization capabilities of the applied techniques, however, convergence issues and stopping criterion were not discussed.

A Lagrangian relaxation approach was also presented in [38]. The dual problem was solved using a Lagrangian relaxation approach with a disaggregated bundle method. In order to improve the performance of the bundle method, a warm-starting procedure was also introduced. Results showed better convergence characteristics compared to the aggregated bundle methods although the implementation was only run on a simple system.

In [39], a comparison of Lagrangian relaxation and truncated dynamic programming methods was presented. The comparison was performed based on the time required for the two methods to reach a near-optimal feasible solution. In spite of the fact that the dual optimal solution obtained by the Lagrangian relaxation method was not always satisfied, it was found to be more flexible for large-scale problems with lower cost than the truncated dynamic programming approach. The approach presented in [40] was a Lagrangian relaxation technique based on variable splitting to solve the hydro-thermal scheduling problem in large-scale predominantly hydro-electrical systems. The problem was decomposed into a set of sub-problems; hydro, thermal and electric. In this approach, the resulting dual problem was non-differentiable and could be solved using a bundling method. A final feasible solution was found by an augmented Lagrangian relaxation technique. However, some infeasibility was still recognized due to the representation of nonlinear constraints by a piecewise linear approximation. The common problem of oscillatory effects associated with the Lagrangian relaxation technique could also be pointed out. Another decomposition method, which is widely applied to solve the hydro-thermal scheduling problem, is the Benders decomposition method. In this approach, the large-scale problem is usually decomposed into sets of coupling variables and the dual formulation of the sub-problems is employed to find the solution.

A multistage Benders decomposition method was presented in [41] to solve the security constrained hydro-thermal scheduling problem. In this work, the hydro system was modeled considering many details and constraints such as cascaded reservoirs, storage and spillage and other hydraulic constraints. The DC model losses for each line were represented by a piecewise linear function. The approach was applied to a study case considering the IEEE 118-bus system. In an extension to the multistage Benders decomposition, the problem was solved by iterative forward and backward recursions in [42]. Benders cuts approach was applied to approximate the cost-to-go function for each stage. In [43], the strategies for handling infeasibility that may occur during the multistage Benders decomposition iterative process were discussed. Considering not only the DC transmission losses but also the AC power flow, Benders decomposition technique was presented in [44, 45]. This approach studied modeling the transmission network using AC power flow when applied to solve the STHTS problem. Congestion management and quality control of service that are typically presented in large and weakly meshed networks were also considered. The method was tested using a 9-bus system and an actual power system. It was considered to have robust convergence properties although, as expected for Benders decomposition method, there was a tailing off effect and slow convergence. To help in reducing the computational times, an accelerating technique was included in the scheme and presented in [45].

2.2.2 Interior-Point Methods

Since the publication of Karmarkar's revolutionary paper [46] in 1984, the field of optimization has been remarkably changed when he rediscovered the interior point (IP) methods [47]. In his paper, Karmarkar proved that IP methods were capable to solve linear programs in a polynomial time manner. He also provided, for the first time, direct evidence that IP methods were faster than the simplex method especially in large-scale optimization problems. The earliest ideas for the IP methods can be traced back to 1955 when Frisch [48] proposed a log barrier function to replace the linear inequality constraints. Gill *et al.* [49] explained the relationship between Karmarkar's method and Fiacco and McCormick's classical logarithmic barrier method.

In general, IP methods can be categorized as; projective methods, affine scaling methods or primal-dual methods [50]. The primal-dual algorithm was first outlined by Megiddo [51]. This “primal-dual path following” approach proposed that the optimal solution should follow the center path. In 1992, Mehrotra [52] proposed the predictor-corrector technique to be integrated with the “interior point path following” methods. IP methods have been applied to solve the problems of power system optimization since early 1990’s. Clements *et al.* [53] was the first who applied IP methods to power system in 1991. In his research, Clements applied a nonlinear programming interior point approach to solve the state estimation problems in power systems. Afterwards, a large number of papers tackling the subject of the application of IP methods in various fields were introduced. A review of the IP methods that were applied to a variety of power system optimization problems up to 1993 is presented in [12]. IP methods have been successfully applied to power system operation and planning areas such as economic dispatch, unit commitment and hydro-thermal scheduling problems. In addition to long and medium-term hydro-thermal scheduling, IP methods have been also employed to determine the optimal short-term schedules for hydro-thermal systems. An updated review on the application of IP methods is presented in [54].

Palacio *et.al* in [55] proposed a primal-dual IP method to solve the STHTS problem and studied the influence of the bilateral contracts and spot market on the optimal scheduling. Transmission losses of each power transaction were calculated and the effects of the loading order on the transmission losses allocated to the pool and bilateral loads were studied. To validate the results, two test systems were used; a 6-bus system and a 27-bus system that was assumed equivalent to a specific real system. Various thermal and hydraulic constraints were considered, but some were not addressed such as the down and up ramp rates.

A genetic algorithm was combined with a primal-dual IP method in the methodology of [56]. In this reference, the determination of the on/off status of the thermal units was performed using the genetic algorithm while the IP method was employed to solve the economic dispatch problem in order to solve the STHTS problem. Results showed that the total available hydraulic energy could not be used because of the hydraulic and generation constraints. Inter-temporal constraints caused by cascaded reservoirs and maximum up and down ramps were among the constraints considered while the transmission system losses were not. Robustness and speed of convergence of primal-dual and predictor-corrector IP methods were studied in [57]. To solve the STHTS problem, the two IP methods were implemented and both were reported to be robust and fast when tested. In this implementation, the thermal system related constraints were not involved because the model considered a predominant hydro system. Costs of startup and shutdown of thermal generating units and the minimum up and down ramp rates were taken into consideration. In order to make it simple, the model used only pure quadratic cost functions for generation considering the same quadratic coefficients for all units. In a conclusion on the convergence issues, the results showed that the number of iterations required was increased by the active bounds, while the generation costs were found to be more critical than the transmission costs and therefore led to faster convergence.

In [58], the objective of the STHTS problem was to minimize the difference between the generation costs and the consumer benefit in a predominantly hydro-electric system considering the dynamic restrictions of the consumer energy constraints. To achieve this goal, a primal-dual IP method was used and the STHTS problem was treated as a single problem. It was found that as the price-responsive load increased, the hydro generation therefore increased and as a result the thermal generation decreased which reduced the generation costs. The authors in [59] proposed an STHTS model in which the spot market trades and the bilateral transactions were discriminated. A primal-dual IP method was employed to solve the hydro and thermal sub-problems and a bundle method was implemented for the dual problem. In this method, the unit commitment status was assumed known. Although the power balance equations did not include the system transmission losses, they were assumed to be supplied by the pool. The hydropower was modeled as a function of the forebay and the afterbay elevation but without considering the flow losses and the effects of the net head and the discharge rate on the joint efficiency of the turbine-generator.

Troncoso *et al.* in [60] used a genetic algorithm to compute the optimal STHTS problem and compare its performance to that of the IP method. Results showed that the genetic algorithm reached better feasible minima while the IP method achieved better performance in CPU time. It was also shown that the IP algorithm including the constraints converged without difficulty when the problem was solved only to obtain an initialization point. On the other hand, when the same problem was solved using the former solution, the stopping criteria needed more iterations. It should be mentioned also that the constraints did not include the system power losses.

The need to decrease the computational burden of the genetic algorithm was expressed as an important issue for real systems. Reference [61] presented a homogenous IP method to solve the STHTS problem. Many constraints were considered in the model assuming that there existed a local large reservoir for each hydro generation unit so that the head variations were ignored. The long-term bilateral contracts and the forecasted market hourly prices for day-ahead auction were integrated in the model. In this implementation, a large-scale system with large number of constraints and variables was used to evaluate the algorithm.

2.2.3 Mixed Integer Programming

Integer and mixed-integer programming have been widely applied to solve different optimization problems such as the hydro-thermal scheduling problem. The commonly shared characteristic of these problems is having continuous and discrete variables that could only take an integer value. Branch and Bound (B&B) and cutting plane are among the most widely applied mixed-integer programming methods.

The STHTS problem is one of the most complex mixed-integer programming problems. Several mixed-integer programming approaches and algorithms have been introduced and many commercial solvers are available. To improve the performance of these solvers, a convex hydro-thermal scheduling method was presented in [62]. In this paper, convexity issues of some standard commercial mixed-integer programming solvers were discussed. The nonlinear mixed-integer short-term hydro-thermal scheduling problem was linearized and the conditional constraints such as the on/off status of the generation units, which was a function of the minimum up/down times, were normalized. The method was tested and results were demonstrated to show good solution quality and computational speed although it was concluded that the convergence computational speed could be improved by using a better B&B procedure.

In [63], a mixed-integer model for hydro-electric systems short-term planning was presented. This model was designed to avoid the problems caused by nonlinearity and non-convexity by considering only the points with good degree of efficiency. The problem was decomposed into sub-problems with relaxed coupling constraints. The model was tested practically using a power system consisting of nuclear and hydro generation units with some assumptions were applied and some constraints were not considered for the sake of simplicity. In [64], a mixed-integer programming based algorithm was used to deal with the unit commitment problem while a multi-embedded linear programming model was applied to find the optimal scheduling for hydro-thermal systems. Linear programming and network flow programming were used to formulate the multi-embedded blocks. The hydro units were represented by a linear model in which water head was fixed and assumed known. To test the algorithm, it was applied to a realistic large-scale case study and the results showed the total cost of the study. However, no information was given regarding neither the computer memory nor the computational time required by the algorithm although direct methods, in general, are expected to have good convergence properties. The problem of computational time associated with the mixed-integer programming approaches is widely recognized especially when applied to large-scale optimization problem such as the STHTS problem.

An algorithm was presented in [65] to deal with this problem by improving the Branch and Bound (B&B) search method. In order to achieve this goal, an initial feasible integer solution was provided to lead the B&B to the optimal solution. An under-relaxed procedure was applied to the hydro-thermal system entirely to overcome the oscillation problem. The algorithm was tested using realistic large-scale case studies showing good performance and computational features.

2.2.4 Dynamic Programming

The dynamic programming optimization approach has been extensively used to solve the hydro-thermal scheduling problem because of the complexity of this problem and existence of the dynamic variables. The ability of dynamic programming to overcome the difficulties of the nonlinearity and non-convexity of large-scale systems is another reason for its popularity. In dynamic programming, large size problems, which consist of many state variables and dynamic elements, are decomposed into smaller problems that could be solved independently. With the so called “curse of dimensionality” [10], which is the limited ability to solve large-sized problems with large number of variables, is the main disadvantage of dynamic programming. In spite of this drawback, it has been applied to various power system areas and studied by a considerable number of publications in the literature.

Yang and Chen presented a special form of dynamic programming techniques in [66] to solve the STHTS problem. To improve the performance of dynamic programming and overcome its disadvantages, namely, the high computational time and large memory storage, a multi-pass dynamic programming technique was implemented. The algorithm was tested using real data obtained from a realistic power system containing thermal and hydro units; however, some constraints were not considered. Although the cases tested in this paper did converge into reasonable solutions, there was no indication that global optimal solutions were guaranteed. In fact, the solutions that were reached might be local, especially when we keep in mind that the algorithm used was an iterative-based process.

A multi-pass dynamic programming approach was presented again in [67] by the same authors and applied to a similar hydro-thermal power system but, in this paper, the pumped storage units were included in the system formulation. The same approach was used also in [68] considering the pumped storage units and battery energy storage system which was simulated and integrated into the system. The energy stored in the battery storage system was presented as an additional state variable in the problem formulation. In [69], a similar approach using the multi-pass dynamic programming was presented and tested using real data although results regarding the convergence issues and computational time and memory storage required were not presented in details to be compared with other published work. A solution to the dual sub-problem of thermal and hydro units was presented in [70], which was the second of two papers whereas the first, [71] was devoted to solve the primal problem. A dynamic programming method was used to solve the thermal unit sub-problem while the hydro sub-problem was solved using the approximation in the state space within the multi-pass dynamic programming. The procedure was tested by running a number of simulations and results demonstrated a good performance and improved computational time.

In [72], a multi-pass dynamic programming was integrated with an evolutionary programming (EP) algorithm in order to obtain an improved solution. Two case studies were presented to implement the approach considering, in addition to thermal and hydro units, pumped storage units which either worked in pumping mode or generation mode with no idle times. An extended differential dynamic programming and mixed scheduling approach was presented in [73] to determine the optimal short-term scheduling of hydro-thermal systems. The problem was decomposed into thermal and hydro sub-problems. An analytical approach was used to solve the thermal sub-problem while the extended differential dynamic programming was implemented for the hydro sub-problems. Unpredictable changes in natural inflow and its impact on the total cost were taken into consideration while developing a quick and practical estimation way for this change.

In [74], a priority-list-based dynamic programming was used to solve the hydro unit commitment as a part of the STHTS problem to reduce the dimension of the problem. A successive approximation method was employed to obtain better convergence properties when applied to realistic test systems.

2.2.5 Evolutionary Computing Methods

Based on evolutionary theory and inspired by the principle of "survival of the fittest" [75], evolutionary computation is one of the computational intelligence based approaches that have been applied to solve complex optimization problems [76]. Flexibility and capability to obtain good quality solutions are the advantages of evolutionary computation; however, these are highly affected by computer requirements and convergence characteristics [77]. Several evolutionary computation techniques have been introduced and applied to power system optimization problems, these include; genetic algorithms (GA), simulated annealing (SA), evolutionary strategies, evolutionary programming (EP) and particle swarm optimization (PSO).

2.2.5.1 Genetic Algorithms

Genetic algorithms have been widely applied to power systems since they were introduced by John Holland in his book [78] in 1975. GA is a search technique that searches for a population of solution points starting from an initial arbitrary solution within the feasible region [10]. Genetic algorithms have become one of the most popular approaches because of the many advantages that have been acknowledged such as their ability to handle any objective function with any constraints. Moreover, they are less likely to converge to local minima since their population-based search is a probabilistic transition strategy [79]. On the other hand, their main weakness is the high computational time required for convergence [77]. Various planning and operation problems of power systems have been solved using genetic algorithms such as economic dispatch, unit commitment and hydro-thermal scheduling problems. One of the earliest applications of GA to solve the STHTS problem was presented in [80]. In this work, a GA-based method was applied to the 24-hour ahead generation scheduling of hydraulically coupled units. The GA was used to solve the hydro sub-problem considering the water balance as well as the effects of net head and water travel time delays. A realistic system was employed to test the method and compare its performance to a dynamic programming approach. Results showed good performance with good solution quality and robustness of GA especially in avoiding local minima as it was theoretically stated. A good overview on GA was presented in [81] and applied to determine the optimal short-term scheduling of hydro-thermal systems. In this lengthy paper, a case study system of chain cascaded hydro units and a number of thermal units was used to evaluate the algorithm where the unit commitment problem was assumed solved while the economic dispatch sub-problem was considered. Many practical constraints were included in the formulation, however, the size of the problem of the case study was small and there was no evidence that the algorithm could be successfully applied to larger size problems. The performance of the algorithm was considered good although no comparison with other approaches was carried out in order to evaluate whether the algorithm was competitive or not.

In [82], a diploid genotype GA was applied to the STHTS problem. Unlike the case of haploid genotype based GA, where chromosomal strings of individuals are decoded directly as a solution, in diploid genotypes based GA an individual has two chromosomal strings. The solution here is represented using a pair of binary strings of the same length. A comparison between diploid genotype and haploid genotype GA approaches was performed and the superiority of the first was illustrated based on the results obtained from performing several simulated test examples. Robustness of the convergence and ability to satisfy constraints were also demonstrated although the algorithm was not compared to other methods. A concurrent solution of the unit commitment and the economic dispatch sub-problems in addition to the STHTS problem using GA was presented in [83]. The approach was tested using a realistic system and the results were considered good. Test results for purely thermal systems gave lower costs when compared to those obtained by other methods including the previously implemented GA that presented in the literature, however, no comparison based on computational time was presented.

In [84], the thermal sub-problem was addressed using a priority-list approach while an enhanced GA was used for the hydro sub-problem. Several practical constraints were considered by the hydro model, which was formulated at the unit level in order to be more accurate. The method was tested using a realistic system and proved to be more effective than standard GA approaches. The scheduling problem in [85] was decomposed into three sub-problems; unit commitment, economic dispatching and STHTS sub-problems. To test the method, a test example was employed consisting of hydro and thermal units but no pumped storage units were included. Volume and discharge water constraints were considered as well as spinning reserve and losses, however, some others such as ramp rates were not considered. Results regarding total costs and final volume and water discharge in reservoirs were presented but no information were revealed about the computational time and memory size required.

An evolutionary algorithm called a cultural algorithm was presented in [86] to solve the daily scheduling problem of hydro-thermal systems. The algorithm was compared to the GA method and showed better results in terms of solution quality and convergence behavior. In reference [87], a real GA and a binary coded GA method were applied to solve the STHTS problem and compared from a computational efficiency point of view. The two algorithms solved the problem assuming that the unit commitment was already solved but the economic dispatch was considered in the problem formulation. Two test cases for each algorithm were run, in the first, the valve-point loading effects were considered while they were not in the second. Results supported the superiority of the real coded GA as it showed better performance than the binary coded GA; however, the two algorithms were not compared to other methods.

In [60], a GA was applied to the optimal short-term scheduling where the on/off status of the thermal and hydro units was computed. In order to obtain a guaranteed feasible solution, some heuristics were applied. Several realistic test case examples were employed to evaluate the performance of the algorithm. These examples consisted of a number of thermal units and one equivalent hydro unit but no pumped-storage units were included. Practical electrical and hydro constraints such as ramp constraints were formulated which raised the operating cost when considered. The GA was compared to an interior-point method approach and as expected, the GA gave better feasible minima while the interior-point method showed better convergence properties.

An optimal gamma-based GA was applied to find the optimal scheduling of fixed-head short-term hydro-thermal generation systems in [88]. The algorithm was designed to minimize the GA variables and hence to reduce the computational burden. Simulation results revealed that the proposed algorithm was able to converge with a lower population size and smaller execution time compared to the conventional GA.

2.2.5.2 Simulated Annealing

Although it is not always classified as an evolutionary method, many researchers include Simulated Annealing (SA) techniques under this category. SA, which is a heuristic optimization method, was first introduced in 1983 by Kirkpatrick [89]. Inspired by thermodynamics, SA technique tackles combinational optimization problems by simulating the thermal dynamics associated with the process of gradually cooling metals and forming crystals. Simplicity and ability to represent different objective functions of complicated optimization problems gave rise to the number of publications and applications of the SA techniques in different research areas of optimization. On the other hand, the main disadvantage of SA is the repeated annealing since when an optimal solution is reached it cannot be detected unless another method is incorporated with the SA [77].

SA techniques have been applied to various optimization problems in power systems including unit commitment, maintenance scheduling, transmission networks and distribution systems. Wong and Wong in their paper [90] presented a sequential SA algorithm to solve the STHTS problem considering various hydro and thermal constraints although some other constraints such as ramp rates were not included. To evaluate the algorithm it was applied to a test example, however, it was a small size system consisting of equivalent thermal and hydro plants without including pumped storage units. Results demonstrated the advantages of the SA techniques such as simplicity and capability to handle complex objective functions in addition to the insensitivity to the starting schedule. On the other hand, the well-known drawback of SA, which was the high computational time required, obviously came into sight. To treat this weakness and improve the speed of execution, the authors developed another SA algorithm, which was described as a coarse-grained parallel SA algorithm, and presented it in another paper [91]. The same testing system was employed to apply the developed parallel algorithm and compare it to the previous one. The parallel SA algorithm showed considerable difference in computational time in addition to slight improvement in its performance compared to the former SA algorithm.

In [92], SA was implemented to solve the thermal sub-problem while the hydro sub-problem was solved using a peak shaving method in order to find the optimal short-term scheduling for hydro-thermal power systems. The proposed method was tested using a modified version of a realistic power system and was considered robust with good performance and reasonable conversion time although it was not compared to other optimization approaches.

2.2.5.3 Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary method motivated by the social behavior of bird flocks and fish schools. PSO was first introduced in 1995 by Kennedy and Eberhart [93, 94] as a heuristic algorithm for nonlinear optimization problems. In addition to the advantages of other evolutionary methods such as simplicity and ability to handle complex objective functions, PSO algorithms do not include many parameters to adjust and do not need perfect initial points. On the other hand, PSO is not ideal from a mathematical background viewpoint and it cannot guarantee convergence to global solutions [95]. PSO algorithms have been widely applied to various complex optimization problems including power system operational planning and design problems. A comprehensive survey of PSO applications in various areas of power system optimization as well as a review of the advantages and disadvantages of this approach were presented in [95]. Umayal *et al.* in [96], presented a PSO application to find the short-term optimal generation schedule as a multi-objective optimization problem. In addition to the minimization of operation costs, the formulation of the objective function had to consider minimizing gaseous emission in order to satisfy environmental constraints. Several practical constraints including emission control and the usual hydro and thermal constraints were considered but some of them such as ramp rates were not accounted for. In order to evaluate the proposed algorithm, two testing systems were employed and good performance results were reported. The method was considered applicable for realistic large-scale systems; however, the size of the testing systems was very limited and no evidence was presented to support this statement. Although it was concluded that the proposed solution was simple and required less execution time, there was no information regarding convergence properties neither were there any comparison with previously applied methods.

In [97], PSO application to the short-term hydro-thermal scheduling problem was studied and compared to other meta-heuristic search algorithms. Comparison revealed that the PSO approach was superior as it proved better convergence characteristics and less solution time. In [98], different PSO versions were presented, applied to solve STHTS problem and compared to each other. According to this reference, there were four versions of PSO based on the size of the neighborhood and the formulation of velocity updating. The algorithms were applied to a test system consisting of a number of hydro units and an equivalent thermal unit while no pumped storage units were included. Compared to other evolutionary approaches, the different PSO algorithms showed better performance and in particular, the local versions of the PSO were found best as they could maintain the diversity of population. However, considering only one equivalent unit to represent all thermal units could violate the accuracy when applied to realistic systems. This weakness was remedied in [99] by considering cost characteristics of individual thermal units. To solve the problem, a PSO was applied considering the effect of valve-point loading on the cost function as well as many, but not all, practical hydro and thermal constraints. The algorithm was implemented using a test system that consisted of a number of hydro and thermal units with no pumped storage units were considered. A comparison to a simulated annealing (SA) as well as to an EP method was conducted and showed the superiority of the proposed PSO algorithm.

In [100], an evolutionary PSO based solution was presented to solve the problem of scheduling pumped-storage units in the frame of the solution to the STHTS problem. The proposed approach was a combination of binary version of PSO and a mutation operation in order to help reaching global minima and performing fast convergence. Results obtained from tests demonstrated good quality solutions and convergence properties when compared to other existing applied methods including standard PSO algorithms. In [101], a PSO algorithm was applied to solve the STHTS problem using a dynamic search-space squeezing strategy to improve the optimization process. It was reported that the proposed algorithm had better solution quality and good convergence properties but no information regarding computation time was provided.

2.2.5.4 Evolutionary Strategies and Evolutionary Programming

Evolutionary strategies and EP are two quite similar evolutionary computation methods, were both introduced in 1960, although they were developed separately in parallel [76]. In spite of their similarities, the two approaches still have some differences from genetic algorithms and other evolutionary based methods. Since they were proposed, the two methods have been applied to various power system problems, though not as widely and increasingly as genetic algorithms. Compared to the small number of published work on the application of evolutionary strategies to solving the STHTS problem, several research papers that applied EP techniques have been introduced.

Werner and Verstege [102] proposed what seems to be a unique application of evolutionary strategies to the short-term hydro-thermal scheduling problem. In the formulation of the problem, the researchers considered run-of-river plants and pumped-storage units without decomposing the problem into sub-problems. A hydro-thermal testing system was employed to evaluate the method. The system consisted of pumped-storage units in addition to the thermal units and hydro units that have the ability to store a limited amount of water. Results were considered good as the algorithm showed the ability to solve the problem with good solution quality although the quality of solution was dependent on the initial solutions as is the case in some of the computation methods. It was also noted that there was no indication in the paper that convergence to global minimum could be guaranteed and hence it was concluded that more focus on convergence properties was required.

In [103], a novel EP algorithm was presented and applied to the STHTS problem. The performance of the proposed algorithm was compared to that of gradient search, genetic algorithms and simulated annealing methods and was reported to show better results in terms of cost as well as computational time and memory size requirement. Two example systems were used to test the algorithm consisting of hydro units and thermal unit while pumped-storage unit were not considered, however, the size of the systems was relatively small. Another comparison between the EP algorithm and the classical gradient search and simulated annealing techniques was presented in [104]. Although results agree with those of the previous reference regarding a lower cost and more powerful searching compared to gradient search and simulating annealing methods, but in contrast, longer execution time was required for convergence than that required by the other two methods.

Reference [105] presented an application of several evolutionary based methods including an EP algorithm. In this work, in addition to the usual constraints, environmental aspects were also taken into consideration as well as ramp rates and transmission losses. The algorithms were applied and compared to classical methods whereas results were considered good although no detailed presentation was offered about the testing system and its size, about neither the comparison results nor the convergence behavior. A constructive EP method, which was a combination of dynamic programming and evolutionary programming, was presented in [106] to solve the scheduling optimization problem of multiple storage hydro-thermal systems. In this method, the problem was decomposed into several sub-problems with cost-to-go functions assuming linear variables and constraints. The method was tested using two case study systems with multi-storage plants. It was found robust, efficient and suitable for a rapid optimal scheduling of practical and large-size systems although, nonlinear, non-convex and non-smooth characteristics of realistic systems were not accounted for when tested.

In addition to classical and fast evolutionary algorithms, that are Gaussian and Cauchy mutation-based respectively, an improved faster EP method was presented in

[107]. In order to evaluate and compare the three algorithms, various aspects were studied such as the effect of the initial solutions and computational time in addition to minimum and mean cost. Effects of valve-point loading and prohibited hydro-discharge zones on hydro-thermal scheduling with quadratic thermal cost function were explored. Results revealed the superiority of the proposed improved fast evolutionary algorithm over the other two EP ones. It should be pointed out that the case study used to apply and implement the proposed algorithm was very small-size system and there was no proof that the same good results could be obtained if applied to practical large-scale complex systems. The same results were obtained and presented by the same authors in [108].

In [109], a hybrid EP-based algorithm was presented to solve the problem without decomposition into sub-problems. The algorithm was tested using sample cases and results lead to a conclusion that the algorithm was an efficient and advantageous method to solve the problem although the test examples were very small-sized and no evidence was indicated to verify that the results and conclusion drawn would hold for complex large-size systems. Besides, many practical aspects and constraints were not taken into consideration including pumped-storage units and ramping limitations. Convergence properties as well as computational time and memory size required were not discussed in the paper although the execution time was judged acceptable. Another application of hybrid EP was proposed in [110] using a novel EP in the first phase and a direct search was used in the second phase. In order to validate the proposed algorithm, it was tested using a small size example and compared to other methods. Results showed that the proposed algorithm provided better cost results and less computational time in addition to robustness and effectiveness. However, except for the cost based comparison, no information was presented to support other results and conclusions. An EP algorithm in [111] was applied and compared to a genetic algorithm approach and when tested showed better performance in terms of cost while no details were shown regarding computational time and memory size. A modified differential evolution-based approach was compared to an EP algorithm in [112] when applied to solve the short-term hydro-thermal scheduling problem. Effects of valve-point loading and emission function inclusion were investigated while various thermal and hydro constraints were considered. Results showed the effectiveness of the method based on the optimal costs and emission but no presentation regarding convergence and execution time was offered in details. Another application of differential evolution-based technique for solving short-term hydro-thermal generation scheduling was presented in [113]. The system considered was a multi-reservoir cascaded one with water transportation delays and valve-point effects. Two test systems were used to evaluate the proposed algorithm and compare its performance to other evolutionary algorithms. Comparison results demonstrated the superiority of the proposed algorithm in terms of cost and computation time.

2.2.6 Artificial Intelligence Techniques

In the field of power system operations and planning, very sophisticated computer programs are extensively required. They are designed in such a way that they could be executed and modified frequently according to any variations. Artificial intelligence is a powerful knowledge-based approach that has the ability to deal with the high nonlinearity of practical systems. Among their useful features are the ability to learn and build the experience within a period and the ability to store the knowledge they learn inspired by the human intelligence. Artificial neural networks and fuzzy logic are the most important artificial intelligence approaches that have been applied to the STHTS.

2.2.6.1 Neural Networks

A neural network is a massively parallel-distributed processor that has the ability of learning and storing knowledge and making it available for use through resembling the human brain in some aspects. The learning process is performed by a learning program that changes the synaptic weights, which are the inter-neuron connection strengths where knowledge is stored, to attain a desired design objective. Once the network is trained, it is capable of generation. Generation refers to the capability of the neural network producing "reasonable" outputs for inputs encountered during the training process [114].

Neural network techniques have extensively been of a great interest to power system community since not very later than the publication of remarkable Hopfield's paper in 1982 [115] . By the late eighties and early nineties, the application of neural network in various power system areas has become quite well established [116]. It should be noted that most of the implementations in the literature are based on the feed-forward multilayer networks [77]. Although other architectures have also been investigated, they are few in number. In spite of the popularity of neural networks in power systems, quite a few papers have been published that applied this technique to solve STHTS problem. Naresh and Sharma [117] proposed a two-phase neural network-based method to find the optimal short-term schedule for hydro-thermal systems. In this implementation, the neural network seemed to be a feed-forward network although its structure was not indicated. The states of the analogue neurons were employed as scheduled discharge for the hydro units. Several hydro and thermal constraints taken into consideration including water transportation delay between cascaded reservoirs and transmission losses although some others were not accounted for such as ramp rates. The method was applied using a test example consisting of multi-chain cascaded hydro units and an equivalent thermal unit while no pumped-storage units were included. The performance of the method was compared to the results obtained by an augmented Lagrangian method and found very close to each other. In [118], a Hopfield neural network was applied to the problem considering a system with fixed-head hydro units and a piecewise linear relationship between the water discharge and the electrical power output function. A test system with two hydro plants and two thermal plants was employed to validate the proposed method and to compare it to Newton's method. Results showed that the two methods did not give different cost results, but no comparison regarding neither convergence characteristics nor computational time was offered. In spite of that, it was concluded that the proposed method was fast and required small computational resources in addition to its efficiency and practicality. It should be also noted that the formulation of the problem did not consider some realistic constraints and the used test example was not large enough to give an evidence that the method could be successfully applied to real word large-scale problems in addition of not considering pumped-storage units.

Pumped-storage units were included in the formulation of the problem presented in [119]. In this paper, an enhanced merit order and an augmented Lagrange Hopfield neural network were presented and applied for the STHTS problem considering various constraints. The merit order was enhanced by heuristic search algorithms while the energy function of the Hopfield neural network was an augmented Lagrangian based function. The method was evaluated using a system with a number of hydro and thermal units as well as pumped-storage units and results were compared to those obtained by other methods such as Lagrangian relaxation and quadratic programming methods. Superiority of the proposed technique was demonstrated in terms of production cost and computational time requirement noting that the comparison was run considering only CPU chip frequency as a common base between the different methods in order to perform a reasonable and fair comparison.

2.2.6.2 Fuzzy Logic-Based Methods

The idea of fuzzy sets was first introduced by Zadeh in 1965 as a generalization of classical set theory [120]. Fuzzy sets use membership functions to map elements of universe of discourse to the unit interval [0, 1]. The membership function always reflects the features and limitations of the studied system so that the fuzzy set accurately represents the problem and makes it easy to understand by non-experts [77]. Fuzzy sets has been applied to various power system areas such as operational planning, state estimation and load forecasting to represent uncertainties by fuzzification of ambiguous variables and employing membership functions that represent system characteristics [9]. A comprehensive practical guide to the fundamentals and application issues can be found in [120] as well as in other published works such as [121-123].

Surveys on the application of the fuzzy logic in power systems were presented in [124, 125] . In the area of STHTS problem, the number of published papers is relatively small compared to the other optimization methods. Among those few papers was the one presented in 1996 [126] by Wong and Wong, who proposed a combination of fuzzy set algorithm with a genetic algorithm and a simulated annealing method. A Short-term generation scheduling was formulated considering take-or-pay fuel cost then the formulation was extended to include the economic dispatch problem. A test example was used to demonstrate the performance whereas the heat-rate functions of the generators included the effect of valve-point loading. Another approach that integrated a genetic algorithm and a fuzzy system-based technique for scheduling hydro-electric generation was proposed in [127]. In this application, problem objective and constraints were fuzzified using genetic algorithms in order to gain better-tuned membership functions and hence more accurate representation. The method was tested using a realistic power system and found effective and practical compared to the conventional fuzzy system although some system constraints were not considered. The comparison was based on production cost and computational time between the two fuzzy-based schemes but it was not performed to include other classic methods.

Reference [128] presented a fuzzy decision-making approach to find the optimal short-term schedule for fixed-head hydro-thermal systems considering a multi-objective problem. In the formulation for the objective function, not only the cost was to be optimized but also the gaseous emission should be minimized in order to meet the environmental regulations. However, these objectives were manifold and hence a weighting technique was applied to satisfy them all in a non-inferior range. To evaluate the method, three testing case studies were employed to demonstrate the effectiveness and flexibility of the algorithm. Issues like computational time and memory size as well as convergence properties were not focused on although it was pointed out that the high computational time required for the complete solution was a limitation. Another formulation of short-term scheduling as a multi-objective problem was proposed in [129] considering the emission concern. In this paper, an interactive fuzzy satisfying method based on an EP technique was proposed considering multi-reservoir cascaded hydro units and non-smooth characteristics of thermal units in addition to emission and other hydro and thermal constraints. The trade –off between the diverse objectives in the non-inferior domain was obtained by the fuzzy satisfying method instead of using weighting methods as in the previous reference. The method was validated using a testing system consisting of a limited number of hydro and thermal units and results were presented although no detailed information was offered regarding convergence behavior or computational time requirement.

2.2.7 Optimal Control and Other Methods

In addition to the work presented in the previous sections, other approaches that dealt with the STHTS problem have been proposed. It should be noted that some of these approaches that combined different techniques with one of the methods stated earlier are already mentioned in the preceding sections. Among the other methods is the optimal control theory that was used to solve the STHTS problem in [130-132]. Optimal control theory is an analytical optimization method that was formulated by Lev Pontryagin and his coworkers [133]. This approach uses differential equations to minimize a cost function by identifying the paths of state and control variables. The optimal control trajectory can be derived using Pontryagin's maximum principle as a necessary condition or by employing the Hamilton-Jacobi-Bellman equation as a sufficient condition. References [3, 134] present a detailed explanation of the application of the optimal control theory in hydro-thermal scheduling optimization problem. In [130], it was shown that in spite of satisfying the ramp rate constraints when solving the STHTS problem, energy delivery capacity is not realized. The maximum principle was applied to formulate a set of equations to determine the energy delivery over the scheduling interval. The objective was to verify the realization of the energy delivery schedule in real-time operation. Although the objective was different from that of the conventional STHTS problem, the effort was to show that physical ramp-rate is not equivalent to energy delivery capability as it was traditionally assumed.

Another application of optimal control theory to solve the STHTS problem was proposed in [132]. In this paper, Pontryagin's maximum principle, with the Bolza-type functional, was applied to prove a condition for the boundaries of the functional. The authors assigned a cost to the water to be included in the cost function instead of only considering the thermal cost. The Gauss–Southwell-type selection scheme was applied so as only the largest gradient value in the gradient vector was considered instead of following the direction of the negative gradient. To apply the method a Mathematica package program was used to solve hydro-thermal system consisting of eight thermal plants and one hydro-plant of variable head. Two tests were carried out considering the same eight thermal units and 10 and 20 hydraulic plants respectively with the same variable-head model. Although it was reported that the method achieved good convergence and only two additional iterations were required when the number of plants was doubled, but the method was not tested for systems with a significantly larger number of hydraulic plants. In addition, it was not applied to hydro-thermal systems with pumped storage units.

A different approach to solve the STHTS problem using a nonlinear network flow model was presented in [135]. This model had linear side constraints and the problem was not decomposed into hydro and thermal sub-problems. The hydro-thermal scheduling problem was formulated as an undecoupled problem while considering the network constraints as well as the local and spinning reserve coupling constraints. To evaluate the method it was implemented using several case examples. The results indicated that the solution was efficient and the computation requirement was reasonable. To evaluate the performance of the method, a general optimization code was used to solve the same problem. However, no comparison with a well-known standard optimization method was presented. Reference [136], presented an approach to improve the thermal start-up and shut-down costs of hydro-thermal systems. This approach was applied using a program package that was not described clearly in the paper. It was indicated that the method was applied to a realistic system although no details about the model were presented. The method was reported to have a beneficial impact on the performance and overall cost; however, no numerical results were demonstrated.

2.3 MULTI-OBJECTIVE GENERATION SCHEDULING

The aim of this section is to present an up-to-date literature survey on the methods and approaches applied to solve the multi-objective optimization problem of the power generation scheduling considering environmental aspects. This includes economic-emission dispatch of all-thermal and hydro-thermal generation optimization problems. It is worth mentioning in this regard that most of the work published considered all-thermal generation systems while not many treated the hydro-thermal generation scheduling. The papers presented in this section have been published during the last 15-20 years (based on IEEE/IET/Elsevier databases). According to the solution method, the reviewed papers are divided into three categories which are; deterministic methods, artificial intelligence techniques, and evolution-based algorithms.

2.3.1 Deterministic Optimization Approaches

Deterministic methods are widely used in solving various optimization problems due to their solid establishment and formulation. These calculus-based methods have been extensively applied to multi-objective optimization problems for at least half a century [137]. Several reviews are available in the literature on the use of classical methods for multi-objective power system optimization problems. Talaq and El-Hawary in 1994 published a paper on the algorithms of environmental-economic dispatch in electric power systems since 1970 [138]. This paper offered a summary of the work that had been published on the economic-emission dispatch although it did not offer an exhaustive list of references on this research area.

Gent *et al.* developed an algorithm to minimize NO_x emission using a Newton-Raphson-based approach [139] . In their paper they applied an incremental loading technique to minimize the gaseous emission. Another attempt to optimize the emission dispatch was presented in [140]. This was conducted by applying Kuhn-Tucker conditions utilizing an air diffusion model. A method was described in [141] for optimal generation scheduling in such a way to comply with the environmental aspects. Reference [142] presented a dynamic emission management system for the sulfur oxide emissions from fuel fossils of the generators. The approach utilized an automatic multiple-strategy selection to control the emissions via generation shifting. To validate this system, it was tested and implemented using a nonlinear convex programming algorithm.

A decision approach was applied in [143] to control the pollution emission from the generating units. Cost-emission trade-off curves were produced for a realistic system with several demand levels and various weather conditions. The computational issues and the implications of the results were the main focus of the paper and hence they were analyzed and reported. In [144], a description of a method for economic load dispatch and optimum mix ratio of high and low sulfur fuels was presented. The idea was based on the assumption that there were two types of fuel; low sulfur but high-priced fuel and a lower-priced but with higher sulfur fuel. Based on Kuhn-Tucker criterion, a coupling method is applied for this problem in addition to the decoupling method used for online control. The impact of pooling arrangement types on economic cost and emission were analyzed in [145]. To assess this impacts, cost-emission trade-offs were obtained using different economic dispatch models.

An algorithm was proposed in [146] to solve the multi-objective problem including reliability, economic dispatch and emission minimization objectives. A set of non-inferior solutions is obtained using ε-constrained technique. The IEEE 30-bus, with 6-generator system was employed to test and validate the performance of the algorithm. Nanda *et al.* applied a linear and nonlinear goal programming technique in [147] to solve the economic-emission dispatch problem. In this approach the two objectives were treated and analyzed separately. A sample 6-generator system was used to test the technique and demonstrate its effectiveness. However the power transmission losses were not included in the problem formulation. In [148], a model was proposed to evaluate the cost and employment impacts of effluent dispatching and fuel switching in order to minimize emissions. The model employed probabilistic production cost methods to consider emission dispatching and fuel switching. A third objective was also considered in addition to the economic-emission objectives. These three objectives were treated by applying the weighting approach via the linear programming. Trade-off curves were computed and analyzed using practical generation system.

The multi-objective stochastic function in [149] considered the uncertainties and inaccuracies in the production cost and emission as well as system losses by reducing them into a deterministic method. Non-inferior solutions were produced using an ε-constraint approach and a trade-off function between conflicting objectives. The method was applied to a selected generation system and the expected minimum cost and emission were reported among the results. However, the validation of the method was demonstrated using only one sample 6-generator system. In [150], a decision making technique was proposed to determine the multi-objective function optimization. The economic dispatch and environmental marginal cost are optimized using Powell's method while the Goal programming was utilized for the trade-off between the conflicting objectives. No more than one generation system with 5 thermal generating units was employed to test the method and demonstrate its performance.

The hydro-thermal scheduling problem was treated in [151] to minimize both cost and emission. A simplified direct method was proposed to minimize these two non-commensurable objectives considering various water availability constraints. A single example of a hydro-thermal generation system which included 4 thermal and 2 hydro units was employed to test the proposed method without considering the transmission losses. Although no information regarding the execution time was mentioned in the paper, the proposed algorithm was claimed to be fast and potentially applicable for real time operations.

Various methods for emission minimization were summarized and analyzed in [5] considering the underutilization provision of the 1990 US Clean Air Act amendments. As a result of the presented analysis, practical methods were proposed for cost estimation and real time operation considering the regulatory constraints. The Clean Air Act of 1990 and its impact economic-emission dispatch problem was discussed also in [6]. The problem was formulated in light of the environmental regulations in order to provide evaluation tools for the different compliance and plants. More analysis of the regulations related to emission minimization was presented in [152] where a simple model for assessing emissions reduction options was proposed. The issue of the existing capacity and its impact on the pollution reduction strategies were discussed and considered in the model design.

The multi-objective economic-emission load dispatch formulated in [153] considered line flow constraints by expressing them in terms of active power generation using distribution factors. Although transmission losses were considered in the power balance equation, some other practical constraints were not included. The emission dispatch was included as a constraint in the classical economic dispatch problem presented in [154]. An efficient weight estimation technique was also utilized in this approach. A discussion on the advantages and disadvantages of different methods was also offered in this reference. Although the iteration results for the emission dispatch were illustrated, but no information about the convergence characteristics or the computation time was presented.

In [155], the environmentally constrained economic dispatch was considered in view of the Clean Air Act of 1990 using the Lagrangian relaxation method. A large generation system with huge number of thermal and hydro generating units was used to validate the proposed method. It was reported that the method had the ability to handle various constraints and accommodate different environmental considerations and regulations. In addition, the method was considered to be fast and accurate although no figures were demonstrated to support this claim. Dealing with the 1990 amendments to the Clean Air Act was the subject of [8]. A set of emission models suitable for cold start, thermal cooling and banking was defined. In addition, an algorithm for emission dispatch was presented to find the minimum cost by restricting the generating units with the emission-cost highest incremental ratio. A small 3-plant, 9-unit, 6-hour system was employed to test the method. In the period of six hours, a maximum reduction of 1.9 and 16.1 percent of SO_2 and NO_x respectively was reported. In various case studies of the system no information on the convergence properties or computation time was illustrated. In [156], to consider the emission, a proxy cost of emission η was added as a Lagrangian multiplier so that the system would operate at the same value of η all the time. The η multiplier was defined as the relationship of the change in cost and the change in emission in a particular hour. Numerical results showed the performance of the approach by presenting the annual cost and emission reductions; however, no information regarding system network losses, convergence characteristics or computation time was reported.

As in [149], the authors of [157] formulated the classical economic dispatch problem considering the emission reduction using the ε-constraint form to trade off between the objectives for different non-inferior solutions. In addition, they used the surrogate worth trade-off method to determine the best solution. A single 6-generator system was used to validate the effectiveness of the method considering the network power losses in each of the various minimization cases. In all cases, results were illustrated without showing the convergence properties or the execution time of the method.

2.3.2 Artificial Intelligence Techniques

Artificial neural networks and fuzzy logic-based methods are the two artificial intelligence techniques used to solve multi-objective generation-emission optimization problems.

2.3.2.1 Neural Networks

King *et al.* developed a simulator to apply the Hopfield neural network for solving the economic-environmental dispatching of thermal generating units [158]. The objective was to find the optimal solution in a minimum number of iterations. In addition, guidelines were offered for selecting the network parameters and the sigmoid function. To exemplify the concept and validate the methodology, several test systems were implemented considering the transmission power losses of the system. The downside of the method is the increase in the number of coefficients of the Hopfield model even when the problem is not large-scaled. It was found that the computation time required for the Hopfield model was the same as such required for the Newton-Raphson algorithm although the computation complexity in the iterations was less.

In [159], a back-propagation neural network was used to find the optimal economic-emission dispatch for thermal generation systems using price penalty factor. The only gaseous emission on which the paper focused was the nitrogen oxide as it was the main globally major issue. The economic-emission multi-objective problem was formulated as a combination of fuel cost and implied cost of the NO_x emission through the augmented price penalty factor. Some of the constraints including the transmission losses and generation limits were considered in the problem formulation while other practical ones were not. To test the method, three thermal generation systems were used but no comparisons of the performance and results with those of other methods were conducted.

As an attempt to overcome the numerical complexity associated with the parameters of the neural networks, a hardware-based implementation of neural networks was proposed in [160]. In this implementation, a scalar function was created to represent the two objectives using a weighting technique. The problem optimal solution was obtained through adjusting the weighting coefficients. The method was tested using a small all-thermal generation system of 3 generating units without considering the transmission losses in the formulation. In another attempt to address the limitations of the conventional neural networks such as the slow convergence, the authors of [161] proposed a more real time-oriented neural network. Their approach was a combination of adductive reasoning network and decision approach. A trade-off strategy to find the best non-inferior solution was also proposed based on an index to measure relative distance from the "ideal point". Two case systems were implemented to find the optimal economic-emission dispatch and to test the performance of the proposed technique demonstrating its superiority over conventional neural networks.

As in [159], a price penalty factor was applied by the Hopfield neural network to solve the economic-emission optimization problem in [162]. The bi-objective function was treated as a single one and a solution was obtained considering the transmission losses and accounting for minimizing the NO_x emission [128, 163, 164][128, 163, 164].

An integrated neural network-based approach to solve the economic-emission bi-objective optimization problem was proposed by Chen *et al.* in [165]. This approach was a combination of a goal attainment method and an adaptive polynomial network to find optimal solutions. In addition, the polynomial networks were integrated statistical techniques to form a learning scheme for the input-output relationship. To test the proposed method and to compare it to the classical neural network, it was implemented using two different systems considering the network active power losses and the valve-point effects.

In [166], a feed-forward back-propagation neural network was implemented to solve the combined economic-emission dispatch problem. The network was trained using the results obtained from using the Lagrangian multiplier technique which was employed to solve the problem initially. An investigation on the computation time and quality of solution in terms of the network parameters was carried out. The proposed technique was tested using a 6-generator system and with various network parameters such as number of hidden layers and number of layers. The proposed network was reported to be up to 12 times faster than the conventional neural network after sufficient training. It should be noted, however, that the price penalty factors used were fixed for each emission condition.

2.3.2.2 Fuzzy Logic-Based Methods

A multi-objective function was treated in [167] to find the optimal scheduling for all-thermal power generation systems. The multi-objective function did not only consider cost and emission minimization but also security and reliability aspects. An expert fuzzy set system was proposed to find the optimal solution for a dynamic generation dispatch problem. The multi-objective problem was transformed into a single objective to obtain Pareto optimal solutions using fuzzy logic. The technique was tested using a moderately-sized system and the performance was assessed using various membership functions. Compared to classical methods, the proposed fuzzy-based approach resulted in much less computation time as reported in the reference.

Dhillon *et al.* in [163] proposed a fuzzy decision making method to determine the long-term hydro-thermal generation scheduling considering emission minimization. In fact, the multi-objective function had three objectives including minimizing the unsatisfied load demand, in addition to cost and emission, over the scheduling period. To obtain the non-inferior solutions, the problem was transformed into a scalar one using the weighted min-max technique. The fuzzy logic was applied as a decision making scheme to find the optimal generation scheduling. A four-thermal and three-hydro generation system was used to apply the proposed fuzzy logic-based technique considering transmission losses. The same approach of the previous reference was applied by the same authors to solve the multi-objective optimization problem for the short-term hydro-thermal generation scheduling in [128]. Three fixed-head systems were studied to test the method considering power losses. As a result, it was reported that the approach could be suitable for any number of objectives and the number of iterations required was small. However, these conclusions were drawn in light of the results obtained using only one case study. In [168], the multi-objective all-thermal power dispatch problem was solved using a weighting technique while fuzzy theory was applied to determine the best optimal solution among the non-inferior set. A similar approach was followed in [169] where a Hooke-Jeeves and evolutionary search technique were applied to find the preferred weighting associated with the best solution in the non-inferior domain. A 5-generating unit system was utilized to demonstrate the effectiveness of the proposed method. Assuming that specific fuzzy goals were defined by the decision maker, an evolutionary programming technique-based fuzzy method was proposed in [129] to solve the economic-emission hydro-thermal optimization problem. After applying the technique and obtaining the solution, the reference membership should be updated in order to satisfy the pre-defined fuzzy goals. A single multi-chain hydro-thermal generation system was used to test the proposed method considering various practical constraints such as power losses and valve-point loading effects. Results showed the effectiveness of the method in generating proper Pareto optimal solution although it was applied to only one test system. The average CPU time was reported as 4582 seconds which is high execution time level. In addition, no information was shown regarding the convergence properties and the robustness of the algorithm. In [170], a weighting-based method was used again to produce the non-inferior solutions with the assumption that fuzzy goals were specified for each objective function. Fuzzy logic was employed to determine the preferred optimal point after obtaining the best solution among the non-inferior domain. In addition to cost and emission minimization, a third objective, which was the security index, was considered by the multi-objective optimization problem in [164]. Fuzzy set theory was applied to find the compromised solution among the non-inferior solution set as in the previous reference. Results were obtained by applying the method on a 25-bus sample system of 5 generating units. A comparison of the results with those obtained by other selected methods showed the superiority of the proposed technique according to the results obtained from the single 5-generator system case study. The same authors of [170] presented a similar approach in [171]. In this reference, a fuzzy decision-making methodology was applied again to determine the generation schedule of all-thermal generation system with an economic-emission multi-objective function. The same Hooke-Jeeves method was used to generate a set of non-inferior solutions.

2.3.3 Evolutionary Computing Methods

In order to overcome the drawbacks of the classical calculus-based methods, population-based techniques have recently been extensively used to solve multi-criteria optimization problems. Economic-emission optimization of all-thermal and hydro-thermal generation systems has been determined using various non-classical approaches. These include; genetic algorithms (GA), simulated annealing (SA), evolutionary strategies, evolutionary programming (EP), differential evolution (DE) and particle swarm optimization (PSO).

2.3.3.1 Genetic Algorithms and Simulated Annealing

Wong et al. proposed an SA-based algorithm to solve the multi-objective generation dispatch optimization problem [172]. In addition to fuel and environmental costs, security requirements of the all-thermal system were taken into consideration in the problem formulation. To represent the environmental objective, constant weighting factors were augmented in the pollutant emission objective function. The effectiveness of the method was demonstrated using a single test system assuming the security of supply to be primary concern and neglecting the transmission power losses. An SA technique was also applied in [173] to find the optimal economic-emission load dispatch of fixed-head hydro-thermal generation systems. In this implementation, the multi-objective problem was converted to a single one using the goal-attainment method. It was assumed that the operator had specific goals for each of the objectives. In a similar formulation, SA was used along with an interactive fuzzy satisfying method to solve the fixed-head hydro-thermal economic-emission dispatch problem in [174].

In [175], a GA was applied for the multi-objective optimization problem which was converted into a single objective using the weighting method. System stability and power exchange concerns were discussed considering the economic-emission objective. A heuristic evolutionary genetic-based algorithm was proposed to solve the bi-criteria optimization problem in [176]. The approach was designed to produce the economic-emission Pareto front solutions from which anyone could be selected according to predefined preferences. Three different thermal generation systems were used to evaluate the performance of the algorithm. Results were given in form of trade-off curves that could be used to decide the emission level and corresponding cost according to the Pareto front. The emission objective function was formulated as an inequality constraint in the multi-objective optimization problem presented in [177]. A GA was implemented to solve the economic-emission minimization problem employing fuel switching techniques. Although no figures were provided to show the computation time and convergence characteristics, it was reported that the algorithm was robust, effective and efficient. A GA was applied with the same formulation used in [178] where emission was formulated as a constraint while minimizing fuel cost and wheeling cost of transmission system. In an attempt to avoid the difficulties that conventional GAs suffer from, two hybrid GAs were presented to solve the economic-emission power dispatch in [179]. The two proposed algorithms were basically a combination of GA and SA techniques. Using relative weighting factors, the total emission of various pollutants were combined into a single objective before obtaining the trade-off curves between total fuel cost and emission. A 10-unit all-thermal generation system with its emission included three pollutants; NO_x, SO_2 and CO_2, was utilized to demonstrate the performance of the two hybrid algorithms. In addition, the impact of fuel type switching and hence heat-rate characteristics of generators were also considered in the simulation results.

In [7], heuristics were introduced to GA to enhance the feasibility of solutions of the Pareto front and to reduce computation time. To show the capability of the proposed algorithm, the economic-emission multi-objective problem was solved using a 19-thermal generating unit system. Results were illustrated by trade-off curves for different fuel types although it was not reported that there were wide variety of alternative generated solutions.

Security issues were considered as a third objective in the multi-objective economic-emission dispatch problem presented in [180]. The GA applied in this work was hybridized with an SA technique to perform the selection operation of the algorithm. The proposed hybrid algorithm was tested using two standard systems and a Pareto optimal set of solutions was provided in form of trade-off curves in addition to some statistical data on the convergence property. However, no information was revealed regarding the computation time although it was mentioned that reducing search time was one of the advantages of the algorithm. Another combination of real coded GA and SA was presented in [181] to solve the multi-objective economic-emission dispatch problem. In order to improve the search, a genetic crossover operator and a problem-dependant mutation operator were incorporated with a local search heuristic. Several systems were used to test the algorithm with the results obtained using specific weight factors for each case. It was reported that the complete Pareto set of solutions, providing the trade-off curves, was given in a single run of the algorithm. It was also concluded that the algorithm was extremely fast although no evidence was provided to show that.

Abido proposed a non-dominated sorting GA-based approach to solve the multi-objective economic-emission dispatch problem [182]. A diversity-preserving technique was utilized in order to avoid premature convergence and generate a well-distributed Pareto front set of solutions. The algorithm was tested using 6-generator all-thermal system considering transmission losses and valve-point effects. The performance and results of the proposed algorithm were compared to those obtained by other methods with demonstrating the superiority of the proposed algorithm. The same author solved the same multi-objective problem using a strength Pareto evolutionary algorithm-based approach in [183]. In this attempt he again employed a diversity-preserving mechanism to enhance the convergence quality and a hierarchical clustering algorithm to provide a representative and manageable Pareto optimal set. He also utilized fuzzy set theory to extract the best non-dominated solution among the set of solutions. In [184], the same author presented a comparative study among three evolution-based methods used to solve the problem. These were the non-dominated sorted GA, niched Pareto GA and strength Pareto evolutionary algorithm. In conclusion, it was reported that the strength Pareto evolutionary algorithm had the best computation time and better handling of the multi-objective problem.

In [185], Rughooputh and King proposed a non-dominated sorting GA with an elitist multi-objective evolutionary algorithm to solve the environmental/economic dispatch problem. The elitism algorithm was incorporated to ensure that the fitness of the best solution among the population would not deteriorate over the generations. Elite parents were used to improve the quality of the off-spring and to enhance the convergence of the GA. As a result, the diversity of non-dominated Pareto front solutions was improved. Fuzzy logic was applied to provide the decision maker with a tool for selecting an operating point from the Pareto set of solutions. The same authors applied the elitist algorithm in [186] considering another pollutant as a third objective in the multi-objective economic-emission optimization problem. The GA proposed in [187] was hybridized with a Tabu search algorithm to solve the economic-emission dispatch of all-thermal generation system. The authors' goal of integrating the two algorithms was to minimize the probability of getting trapped in local minima and to improve the convergence characteristics of the hybrid algorithm.

To prevent premature convergence, a fuzzy evaluation factor was applied to the fitness function of the multi-objective GA in [188]. A third objective was included to optimize the system active power loss in addition to cost and emission objectives. In [189], hybrid GA was applied and a binary coded GA was used to search the incremental cost factor. The two-phase algorithm was designed so that the initial solution used for the second phase was the obtained solution of the first phase to reduce the search reason.

Liu *et al.* in [190] developed a kind of immune GA to solve the economic-emission dispatch problem. They represented the objective functions as antigen and solutions as antibody and employed evolutionary strategies to update the population. The economic-emission dispatch was formulated as a stochastic evolutionary multi-objective optimization problem in [191]. The uncertainties and inaccuracies associated with the acquired data were taken into consideration. The GA was applied as an optimizer while a Monte Carlo sampling scheme was used to treat the stochastic decision variables.

A GA equipped with an evolutionary direction operator and a migration operation was presented in [192]. To avoid the deforming of the augmented Lagrange function, a multiplier updating technique was employed. The economic-emission multi-objective optimization problem was formulated using the ε-constraint technique to generate Pareto optimal solutions. To demonstrate the effectiveness of the proposed approach, it was applied to an all-thermal 6-generator test system with the results were illustrated by the trade-off curve of Pareto set of solutions. It was concluded that the proposed method required relatively smaller CPU time compared to the conventional GA. The same author extended the application of the proposed algorithm to solve the economic-emission multi-objective short-term hydro-thermal generation scheduling problem [193]. In the problem formulation, the ε-constraint technique was utilized to generate Pareto optimal set of solutions while the multiplier updating method was used to handle other equality and inequality constraints.

Brar *et al.* applied a GA in [194] to find the optimal active and reactive power scheduling for a multi-objective load dispatch problem. The impact of NO_x on the environment was treated as an individual objective. A fuzzy decision-making technique was employed to determine the fitness of strings in each generation. Fuzzy theory was also applied to panelize the fitness for any violated constraints.

In [195], a non-dominated sorting GA was proposed to determine the optimal operation of a day-ahead electricity market. It was reported that the algorithm was capable of finding the Pareto optimal front in a single run and providing the market decision maker with a realistic and feasible tool to choose the best schedule for the day.

A comparative study on the application of two evolution-based algorithms to solve the economic-emission dispatch problem was presented in [196]. Genetic and ant colony search algorithms were presented, implemented to solve the multi-objective problem and compared to the conventional Lambda iteration method. The Roulette wheel selection and two point crossover were used in the case of the GA but premature convergence was observed although it was reported that its performance was fond better than that of the Lambda iteration method.

In [197], considering the decision maker's goals to search for a Pareto optimal set of solutions, two methods were integrated in a multi-objective GA-based technique. The first was a kind of weighted Pareto method and the second was the so-called guided multi-objective GA. Using this algorithm, the operator preferences were expressed by numerical weights so that the concept of Pareto dominance was extended by biasing the chromosome replacement step of the algorithm. Furthermore, according to the preferred linear trade-off functions, the shape of the dominance region was changed.

In addition to cost and gas emission, a third objective was considered in the multi-objective short-term hydro-thermal scheduling optimization problem presented in [198]. This objective was the optimization of the reservoirs' water spillage. In this implementation, a non-dominated sorting GA was proposed to generate the non-inferior solutions and reflect the decision-makers presences.

2.3.3.2 Evolutionary Strategies and Evolutionary Programming

Wong *et al.* applied an EP-based algorithm to solve the dynamic economic dispatch problem for an all-thermal generation system considering the emission as a constraint [199]. In their implementation, they employed solution acceleration techniques to improve the speed and robustness of the algorithm. Specifically, the "cooling" mutation and population remapping techniques were developed to enhance the performance of the algorithm. To test the algorithm, the authors utilized a 9-generator system with its generators' input-output characteristics were presented by cubic functions considering a 6-interval scheduling period of 1 hour each. Results showed the obtained optimal power scheduling along with the economic-emission dispatch in addition to the statistical information in form of cost-iteration curves. However, no trade-off curves were provided to show the Pareto front set of solutions and no figures regarding the computation times were reported although it was stated that the speed of the algorithm was enhanced. In [200], an EP-based interactive approach was presented to solve the economic-emission dispatch problem of cogeneration systems. The problem was modeled so that the emissions of SO_2 and NO_x were expressed as a function of fuel enthalpy. The formulation considered several operational and fuel type-based constraints such as steam and fuel mix ratio in a boiler which was determined considering the time-of-use dispatch between cogeneration systems and utility companies. The EP algorithm was applied to optimize the single objective function which was obtained by combining the two objectives using the minimum least square error technique. In another attempt, the same author applied the same technique in [201] to solve the problem considering a third pollutant which was CO_2.

Venkatesh *et al.* presented a comparison between EP and two GA-based approachs applied to solve the economic-emission dispatch problem [202]. The problem was solved using the three algorithms considering the line flows that were computed directly using the Newton-Raphson method while a modified price penalty factor was applied to convert and include the objectives in a single function. Simulation results obtained from analyzing several test systems using the three algorithms revealed that the EP algorithm was the best among the three methods in terms of fuel cost. However, no comparison results were reported regarding computation time or convergence characteristics. In [203], an EP algorithm was applied along with a weighting sum method to convert the multi-objective function to a single one. The approach utilized a non-dominated solution ranking method as a selection mechanism for the Pareto optimal solutions. The method was tested using two all-thermal generation systems and trade-off curves and Pareto optimal solutions were obtained in a single run and reduced computation time although no details were explained. In a similar presentation, two of the authors of the previous reference applied the same approach in [204] concentrating on pollutant type in their presentation.

A fuzzy mutated EP algorithm was presented in [205] to solve the emission constrained economic dispatch problem. Fuzzy set theory was employed to provide an adaptive scaling factor for the mutation process in order to avoid premature convergence. A sample 6-unit all-thermal generation system was utilized to test the proposed algorithm with only one pollutant was considered.

Dillon *et al.* proposed a binary successive approximation-based evolutionary search strategy for solving the economic-emission load dispatch problem in [206]. A weighting method was developed and used to find trade-off curves for the conflicting objectives of the non-inferior set of solutions. A fuzzy logic-based technique was used to select the "preferred" optimal solution on the trade-off curve according to the decision-maker preference. The method was applied to several test systems considering various practical constraints such as transmission losses and valve-point effects. According to the results obtained, it was reported that the method achieved better results in reducing emission compared to other methods. On the other hand, its performance was lower in terms of cost and losses minimization.

2.3.3.3 Differential Evolution

Inspired by natural evolution, a DE algorithm was applied to determine the solution of the economic-emission dispatch problem in [207]. Two approaches were presented and applied to the studied multi-objective optimization problem. In the first, the emission objective was formulated as a constraint for the fuel cost minimization single objective function. The second formulation employed the weighting method to convert the bi-objective function to a combined single one. Two test thermal generation systems were used to simulate the problem and test the algorithm and the results were presented including 20- Pareto point trade-off curves. A similar approach was used in [208] where a DE-based for environmentally constrained economic load dispatch was presented. The economic-emission objective function was converted into a single one using a price penalty factor method. The algorithm was tested using a 6-unit system and compared to other methods demonstrating its superiority in terms of fuel cost, emission and losses in addition to CPU time. In [209], a DE algorithm based on a Pareto non-dominant sorting technique was proposed for optimal economic-emission dispatching. Fuzzy set theory was applied to help the decision maker choose, according to predefined goals, the optimal compromised solution from the Pareto optimal domain. A 6-unit thermal generation system was utilized to validate the proposed approach and demonstrate the effectiveness of the algorithm. The resultant optimal solution and economic-emission dispatch were presented along with the Pareto front trade-off curves. In addition, it was concluded that the algorithm's performance was better than that of the conventional non-dominant sorting GA in terms of convergence properties, convergence speed, the Pareto front integrality and the non-dominant solutions' distribution. However, no information was reported to support this claim regarding convergence and computation time.

2.3.3.4 Particle Swarm Optimization

Umayal and Kamaraj used a PSO technique to find the generation schedule of a short-term fixed-head hydro-thermal system considering multi-objective function optimization [96]. The problem was formulated to have five objectives that represented cost, NO_x emission, SO_2 emission, CO_2 emission and variance of generation mismatch with the explicit recognition of statistical uncertainties in the objective variables and power demand. Two fixed-head hydro-thermal test systems were used to validate the proposed algorithm and show its effectiveness. A non-inferior solution with trade-off curves of Pareto optimal set of solutions was generated along with risk levels with the given weighting factors of importance. It was reported that the proposed algorithm required less computation times, however, no figures were mentioned regarding that and no comparison with other techniques was disclosed.

In [210], a bi-criteria global optimization-based approach and a PSO technique were implemented to find the economic-emission optimal all-thermal generation dispatch considering the security requirement of power networks. The proposed algorithm was tested using 3-area interconnected and longitudinal system and trade-off curve was generated to provide the non-dominated solutions. The solution which gave the best compromise among the three objectives was selected as the most appropriate one. Results were compared to those obtained by GA in terms of fuel cost emission and line loss.

Abido proposed a redefinition of global and local best in multi-objective optimization using PSO technique to solve the economic-emission dispatch problem [211]. He applied a clustering algorithm to control the Pareto optimal domain with a fuzzy logic-based mechanism to extract the best compromised solution among the Pareto front set. The proposed approach was tested on a 6-unit all-thermal generation system considering two case studies. In the first case study, the two objectives were optimized separately to find the extreme points of the trade-off surface and investigate the diversity properties of the Pareto optimal set of solutions. Then the proposed algorithm was applied to solve the multi-objective problem by optimizing the two objectives simultaneously. Results showed that the diversity and ell-distribution of the non-dominated solutions over the Pareto optimal front were preserved. Two out of the 25 non-dominated solutions were considered the best cost and best emission as a result of a single run of the two optimization approaches.

In [212], a PSO technique was presented to solve the economic-emission dispatch problem considering the non-smoothness caused by the valve-point loading effects of the thermal generating units. Different weighting factors were assigned to each of the objective functions according to its importance. The one-objective function was then formulated to represent the conflicting objectives through the weighting method. Simulation results were presented in terms of best cost and the corresponding emission release without providing any trade-off curves for the Pareto optimal domain. The performance of the algorithm was compared to those of other evolution-based algorithms and it was reported it had comparable results and very less computational time in spite of the lack of evidence.

Al-Awami *et al.* incorporated wind-generated power in the economic-emission multi-objective optimization problem presented in [213]. They applied a multi-objective-based PSO algorithm to determine the Pareto optimal set of solutions. The testing generation system used to validate the proposed algorithm consisted of two thermal units and two wind farms. A set of the Pareto optimal solutions was generated and the impacts of various operating conditions, such as load level and cost confident values, on these solutions were investigated.

2.4 SUMMARY

In this chapter, an extensive bibliographical survey of work published on the application of different optimization methods used to solve the short-term hydro-thermal and multi-objective economic-emission dispatch problems has been presented. Various optimization techniques that tackled the two problems have been overviewed and classified with their advantages and limitations having been critically discussed. The chapter has provided a general literature survey and a list of published references on the two topics aiming to offer the essential guidelines regarding the scope of the thesis and this active research area. It is noteworthy to mention that a major part of the material presented in this chapter is discussed in [54] and [214].

CHAPTER 3 BACTERIAL FORAGING ALGORITHM FOR OPTIMIZATION

3.1 INTRODUCTION

This chapter presents the proposed modified bacterial foraging algorithm (MBFA) as a powerful heuristic optimization technique. It introduces the modifications and improvements to the basic BFA in order to solve nonlinear constrained optimization problems. BFA is a recently introduced optimization algorithm, which has been successfully employed to solve relatively simple unconstrained problems. However, for constrained larger scale problems, essential modifications are required to enhance the performance of the algorithm. In the following sections, the basic BFA is discussed before introducing the MBFA and the proposed constraint-handling mechanism applied to the algorithm. The chapter begins with a brief introduction to optimization theory and the classification of optimization problems as well as the various solution methods.

3.2 THE CONCEPT OF OPTIMIZATION: AN OVERVIEW

Optimization is the minimization or maximization of a mathematical function to find the best solution while satisfying a number of equality and/or inequality constraints [215]. According to this description, optimization is an important tool for solving various applied science analytical and practical problems. Modeling optimization problems is the key to the process of optimization. In order to construct an appropriate model, an objective must be first identified. This objective, based on the nature of the problem, is the criterion with respect to which the optimization is executed. The optimization objective (also known as merit) could be cost, profit, time, energy, gaseous emission or any other quantity or combination of quantities. It is obvious that the objective function is expressed in terms of specific characteristics of the system, known as decision or control variables. These variables are often restricted by certain limits and boundaries known as constraints [216].

According to the designation, the optimization problem can be mathematically formulated as:

$$\min_{x \in \mathbb{R}^n} f(x) \tag{3.1}$$

subject to

$$\begin{aligned} g(x) &= 0 \\ h(x) &\le 0 \end{aligned} \tag{3.2}$$

where

f(x) : objective function to be minimized

x : vector of variables or unknowns

g(x) : vector of equality constraints

h(x) : vector of inequality constraints

This formulation is expressed as a minimization problem as the objective is to minimize *f(x)*. Nonetheless, it could be also used for optimization problems that require maximization of their objective functions since minimization of *f(x)* is equivalent to maximization of *–f(x)*. Therefore, without loss of generality, this issue can be accommodated by the above formulation although the discussion throughout this thesis will consider optimization as a connotation of minimization.

3.2.1 Constrained and Unconstrained Optimization

Optimization problems are commonly classified depending on the type of the constraints on their variables although other different criteria can be applied. They could, for instance, be classified according to the nature of their objective functions and constraints (linear, nonlinear or convex), the smoothness and differentiability of the function, the number of unknowns … etc.

If, in some situations, it is possible to disregard some constraints because they have no effect on the solution, then the optimization problem is called unconstrained. Unconstrained problems can also come up as a result of trading the constraints by penalization terms augmented to the objective function.

Constrained optimization problems are those subject to constraints on their variables imposed by the nature of the problem and consequently the characteristics of the model. Constraints can be equality or inequality constraints as formulated in Equation (3.2).

They can be boundary, linear or nonlinear constraints depending on the complexity of the relationships among the variables [216].

3.2.2 Global and Local Optima

The function $f(x)$ of Equation (3.1) is said to have a local minimum at any minimizer $x=x^*$ if $f(x^*) \leq f(x^* \pm d)$ for all sufficiently small values of d. The function $f(x)$ is said to have a global minimum at x^* if $f(x^*) \leq f(x)$ for all x (not only for all x close to x^*). The difference between the global and local minima is illustrated in Figure 3.1.

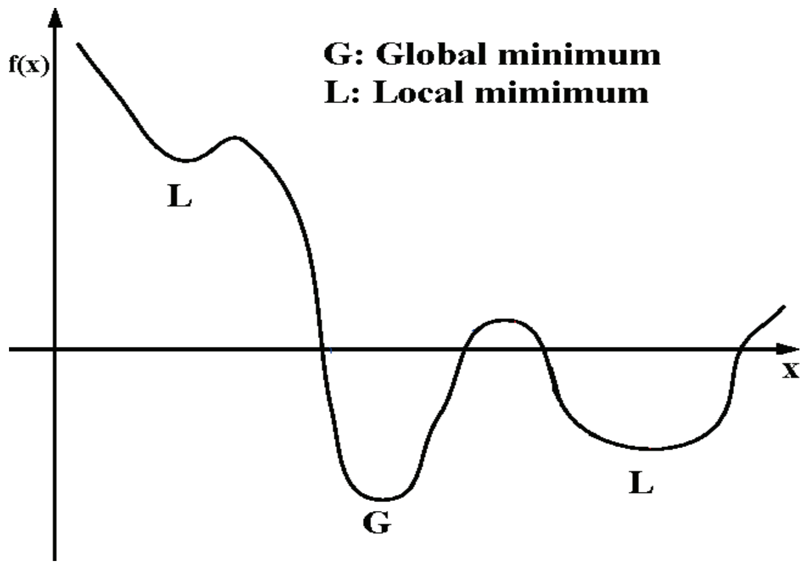

Figure 3.1 Global and local optima.

Optimization algorithms, in general, do not always converge to the global minimum; however, they search for a feasible local solution in the surrounding region such that the objective function is smallest. Global solutions are, obviously, sought after but difficult to discover and arrive at. Nonlinear non-convex problems usually possess local solutions that are not global [216].

3.3 Multi-Objective Optimization

The optimization problem expressed in Equation (3.1) considers not more than one criterion and hence, it is characterized as a single-objective optimization problem. On the other hand, a multi-objective optimization problem has more than one criterion to be treated concurrently [217, 218]. Multiple and conflicting objectives are naturally involved in almost all realistic optimization problems in various operational and planning areas. The subject of multi-objective optimization and its applications in various real-world problems have been of growing interest to many researchers since 1960's [219].

According to the definition of multi-objective optimization, the goal is to optimize a number of conflicting objective functions subject to various constraints. The problem can be formally expressed as follows (minimization approach):

$$\min_{x \in \mathbb{R}^n} \quad f(x) = [f_1(x), f_2(x), \ldots, f_G(x)]^T \tag{3.3}$$

subject to

$$\begin{aligned} g(x) &= 0 \\ h(x) &\leq 0 \end{aligned} \tag{3.4}$$

where

$f(x)$	: a vector of G conflicting objective functions; $f_1(x), f_2(x), \ldots, f_G(x)$
x	: vector of variables or unknowns
$g(x)$	: vector of equality constraints
$h(x)$	: vector of inequality constraints

The feasible domain contained in the criterion space is referred to by Z and the feasible area in the decision space is denoted by the set S, and defined as follows [220]:

$$S = \{x \in R^n \mid g(x) = 0, h(x) \leq 0\} \tag{3.5}$$

$$Z = \{z = f(x) \in R^G \mid z_1 = f_1(x), z_2 = f_2(x), \ldots, z_G = f_G(x), \ \ x \in S\} \tag{3.6}$$

Using Equations (3.5) and (3.6), the multi-objective optimization problem expressed in Equation (3.3) can be represented as follows:

$$\min \quad \{z_1 = f_1(x), z_2 = f_2(x), \ldots, z_G = f_G(x)\} \tag{3.7}$$

3.3.1 Non-Dominated (Pareto-Optimal) Solutions

Unlike the case of single-objective, in multi-objective optimization there is no such a best solution which is superior to other solutions with regard to all conflicting objectives. Any solution can be best for one of the objectives but not for others. In fact, for multi-objective optimization problems there exists a set of incomparable solutions. The solutions in this set are known as non-dominated solutions or Pareto optimal solutions [137]. A non-dominated point in the criterion space Z has an image in the decision space

S, which is called efficient or non-inferior [220]. This can be explained so that a point in the criterion space $z^0 \in Z$ is non-dominated if and only if there exists no other point $z \in Z$ such that:

$$z_k < z_k^0, \qquad \text{for some } k \in \{1, 2, ..., G\}$$
$$z_l \le z_l^0, \qquad \text{for all } l \neq k$$

where z^0 is a dominated point in the criterion space Z. In addition, a point in the decision space $x^0 \in S$, is efficient if and only if there exists no other point $x \in S$ such that:

$$f_k(x) < f_k(x^0), \qquad \text{for some } k \in \{1, 2, ..., G\}$$
$$f_l(x) \le f_l(x^0), \qquad \text{for all } l \neq k$$

where x^0 is inefficient so that its image in the criterion space is a dominated point. On the other hand, an efficient or non-inferior point in the decision space has a non-dominated point as its image in the criterion space. These efficient points form a set of efficient solutions which is known as the efficient frontier. In addition to non-inferior solution, an efficient solution is also called a non-dominated solution or a Pareto optimal solution. The concept of Pareto optimal front and non-dominated solutions are illustrated in Figure 3.2 where points *A* and *B* are non-inferior while *C* is an inferior point.

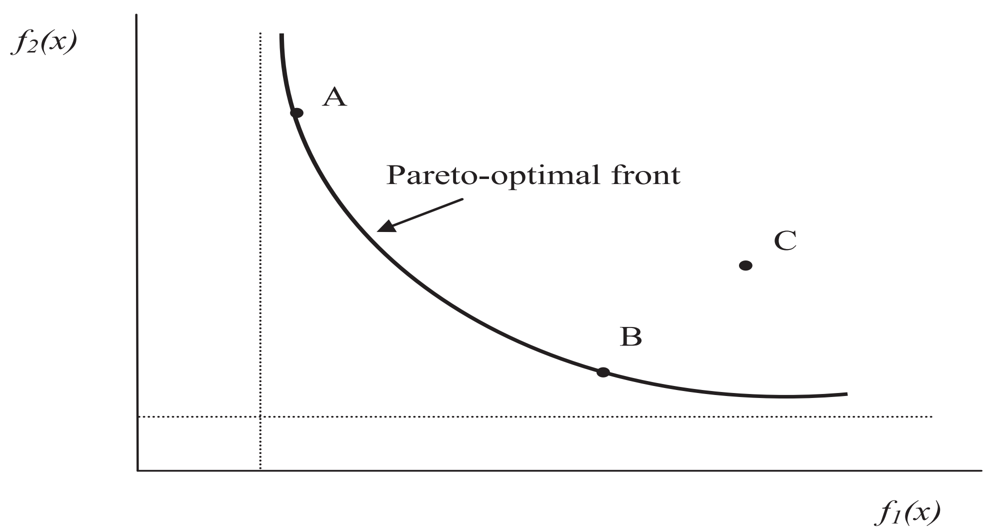

Figure 3.2 Pareto optimal set of solutions.

3.3.2 Solution Preference and Trade-offs

Efficient solutions of multi-objective problems are incomparable with each other as the conflicting objectives are non-commensurable. This means that no single criterion can be applied to treat these objectives at once. In realistic decision-making situations, one of the non-dominated solutions is selected to be the best-compromise solution according to the decision maker preference. The main task of a multi-objective optimization is to find as many Pareto optimal solution points as possible in order to give a wide range of choices among which the decision maker can select the best-compromised solution. In this regard, the set of solutions converged close to the Pareto optimal front must be as diverse as possible to assure that a good set of trade-off solutions among the objectives is accessible [137].

3.3.3 Classical Multi-Objective Solution Approaches

Classical multi-objective optimization techniques have been applied for more than forty years [137]. The goal can be either to find a set of non-dominated solutions or to find a best-compromise one among them. To handle this decision-making process, various methods and algorithms have been applied and classified according to various standards. In general, these techniques are categorized into two approaches [221]; (1) generating methods and (2) preference-based methods. In the first approach, a set of Pareto non-dominated solutions are identified for the decision maker to choose the best-compromise or preferred solution according to some subjective preference. In this case no prior knowledge of preference or importance of any objective is specified. On the other hand, preference-based methods employ some priori-knowledge of the importance of each objective to find a compromise solution. Each of the two approaches has its characteristics, advantages and drawbacks. A good judgment has to be made by the decision-maker to select the best-compromised solution among the Pareto optimal front obtained by the generating approach. Alternatively, in the case of preference-based approach, decision-makers have to formulate their subjective preferences properly and accurately. More amended and revised classifications were suggested by various researchers who have attempted to fine tune the discussed classifications [222, 223].

Traditionally, methods of solution transform multiple objectives into a single one and then solve the optimization problem using various optimization techniques. The following are some of the classical methods that are classified based on preference information:

3.3.3.1 Weighted-Sum Method

The weighted-sum method [224], is applied by multiplying each objective by a pre-defined weight and combining the weighted objectives into a single objective function. This method is considered to be the simplest and most commonly used approach [137]. The weighted-sum method, also called the parametric approach [1], can be mathematically expressed as follows [137, 220]:

$$min \qquad f(x) = \sum_{k=1}^{G} w_k f_k(x) \tag{3.8}$$

subject to

$$x \in S \tag{3.9}$$

$$\sum_{k=1}^{G} w_k = 1, \ \ w_k \geq 0 \qquad (k = 1, 2, ..., G) \tag{3.10}$$

where $w_k (\in [0,1])$ is the weighting coefficient of the k^{th} objective function. The simplicity and easiness to use make this method suitable for finding solutions to problems with convex Pareto optimal front. However, in order to guarantee finding well-distributed solutions on the entire Pareto optimal set, the problem should be solved many times using different weighting values. Moreover, it is reported that the weighted-sum method cannot be utilized for some non-convex objective function spaces. This is because of its incapability to find certain Pareto optimal solutions in some specific cases [137].

3.3.3.2 Weighted Min-Max Method

The weighting coefficients used in the weighted-sum method are utilized in the weighted min-max method as follows [225]:

$$min \left[\max_{1 \leq k \leq G} \ \ w_k f_k(x) \right] \tag{3.11}$$

subject to

$$x \in S \tag{3.12}$$

$$\sum_{k=1}^{G} w_k = 1, \ \ w_k \geq 0 \qquad (k = 1, 2, ..., G) \tag{3.13}$$

3.3.3.3 ε–Constraint Method

The ε-constrained method is used to overcome the difficulty suffered by the weighted-sum method in handling some cases with non-convex objective spaces of some problems. In this method, one of the objective functions is considered the primary while the others are treated as constraints [226]. This is expressed as follows:

$$min \qquad f_k(x) \tag{3.14}$$

subject to
$$f_j(x) \le \varepsilon_j \qquad (j = 1,2,...,G; \;\; j \ne k) \tag{3.15}$$

$$x \in S \tag{3.16}$$

where the parameters $\varepsilon_j \, (j = 1,2,...,G; \;\; j \ne k)$ are the upper bounds of the values of the objective function $f_j(x)$. Choosing the ε parameters is a critically key factor for the success of this method. Therefore, these parameters must be selected so that they lie within the boundaries of the objective functions.

3.3.3.4 Utility Function Method

In this method a mathematical mapping of the points in the criterion space into real numbers is used to represent the preference function. The utility function $U_k(f_k(x))$ represents these numbers so that the greater the number, the more important the objective function [220]. A very comprehensive presentation of the mathematical aspects and applications of the method is presented in [227]. The utility function approach can be mathematically formulated as follows [1]:

$$min \qquad f(x) = \sum_{k=1}^{G} U_k(f_k(x)) \tag{3.17}$$

where $U_k(f_k(x))$ is the utility function of the k^{th} objective function. The utility function should be defined in advance, however; it is not easy to evaluate it, and this somewhat limits the application of this method.

3.4 Optimization Methods for Power System Operations

In Chapter 2, various optimization methods that have been used to solve the STHTS and economic-emission multi-objective problems were reviewed and classified. In this section a brief discussion of optimization methods and techniques is demonstrated. Optimization approaches in general can be classified into two main categories; deterministic and heuristic.

Deterministic methods are calculus-based where the search scheme is to compute a derivative-based operator such as the gradient, Hessian or both. The following discussion, based on references [13, 216, 228-230], is a summary of the most well-known deterministic optimization methods used for realistic problems:

1. Linear programming (LP) methods: These methods are widely used due to the easiness of modeling in spite of the nonlinearities associated with realistic problems. The real system is simplified to build a linearized LP model. The LP problem is then solved using the simplex method or interior point (IP) methods.

2. Nonlinear Programming (NLP) methods: Since it is a fact that most practical problems are nonlinear and non-convex; these methods are needed especially when linearization is not feasible. Sequential quadratic programming (SQP) and generalized reduced gradient (GRG) are the most powerful and well established NLP methods. SQP methods require solving the approximated problem on each iteration and updating the Hessian of the Lagrangian function.

The second category of optimization techniques is the heuristic (or meta-heuristic) methods. These are non-conventional methods that are based on various analogies and mostly inspired by natural phenomena and biological evolution. Among these methods are EP, evolutionary strategies, GAs, ant colony, SA, Tabu search, PSO and BFA. These non-derivative non-calculus based methods have been successfully applied to solve various optimization problems especially when no information about the gradient is available. These methods are superlative for tackling optimization problems with non-differentiable and non-continuous characteristics.

Differences between heuristic and deterministic optimization methods can be observed in the way of search for minima as well as in other characteristics [231]. While deterministic methods use single search paths, heuristic methods execute their search on population basis. They use numerous prospective solution points to explore the hyper search space. In contrast with deterministic methods, which use deterministic transition rules, heuristic methods apply randomness to update their solution vectors. This gives an advantage to heuristic methods in avoiding local minima. Heuristic methods can be used to solve different classes of optimization problems regardless of the nonlinearity, non-convexity or non-continuity of the problem. On the other hand, different deterministic methods are needed for different optimization problems.

A brief description of the most popular heuristic optimization methods was provided in Chapter 2. The following sections are devoted to present a detailed description, and in depth discussion on the BFA as it is the core of the methodology applied in this thesis.

3.5 Bacterial Foraging

The need for powerful tools to solve non-convex nonlinear optimization problems has been an encouraging and consistent motivation. Non-convexity and non-smoothness of accurately modeled optimization problems are challenging characteristics for nearly all optimization methods. In order to deal with such issues and to overcome difficulties from which deterministic methods, in particular, suffer, researchers introduced and developed heuristic techniques. These non-traditional approaches are getting more interest because of their attractive features and promising potential. BFA is one of the recently introduced evolutionary heuristic optimization techniques. This algorithm, which is inspired by the foraging behavior of the *E. coli* bacteria, has been successfully implemented to solve relatively small optimization problems. However, it shows poor convergence characteristics for larger non-convex constrained problems with high dimension search spaces. The basics of the BFA as modeling of the foraging process and as an optimization technique are found in what is known as the foraging theory which will be discussed latter in this section. A biological background of the foraging behavior of the *E. coli* bacteria is explained in this section. In addition, a fundamental BFA as a computer simulation is introduced and analyzed. The discussion in this section is mainly based on the reference [232] in which the BFA is first introduced by Passino in 2002.

3.5.1 Foraging Theory

In nature, organisms and species struggle to maximize their energy intake E per amount of foraging time T when they search for nutrients and obtain food. They, in fact, perform an optimization task in which the objective is to maximize the following function-like:

$$\frac{E}{T} \tag{3.18}$$

Optimization of this energy gain function is of crucial importance for foraging species to survive and perform various on-going activities. Foraging tasks include exploring a patch of food, making a decision to go into and search for food through it and finally to determine when it is time for leaving for a richer location. Depending on many factors, the nature of foraging differs as the foraging organisms are different. For instance, finding food is difficult for some species but at the same time they do not eat much. In contrast, others find food easily but they have to eat much because of the low energy level they obtain from their food. Other factors that affect foraging include some daily activities such as trying to find safer environments and better weather conditions. Performing this optimization process- foraging- is, in most cases, neither an easy nor a safe assignment. There always exist obstacles and constraints that must be accommodated such as rivers, mountains, severe weather conditions, distances between food patches and the existence of predators. Furthermore, the nature of the forager itself determines its foraging behavior. For instance, some foragers are large in size and others are small, some follow specific search rhythms while others search for food only when they need it...etc. Foraging could be also affected by the characteristics of the patches of food or prey that could naturally appear and disappear or move away from the forager.

According to optimal foraging theory [233], foraging can be formulated as an optimization problem, and hence, an optimal foraging principle can be established to explain foraging decision making mechanisms. Although modeling the optimal foraging provides an explanation of what the optimal behavior would be like, some biologists argue that animals are not able to make optimal decisions. On the other hand, biologists reported that animals use foraging decision heuristics extensively and efficiently in approximating optimal schemes considering the existence of constraints [233].

3.5.1.1 Search Strategies

The search strategy, which is the major part of foraging, is the optimization process executed to find food. According to some studies of foraging, a typical scenario for predation is followed by many foragers as their search strategy [234]. Predators search for prey, hit it, and then grip it and ingest it. Depending on the relationship between the predator and the prey, one of these steps is more vital than the others. If the predator is larger than the prey then the search task is most important as small size is an advantage for the prey that makes it difficult to find. On the other hand, if the predator is smaller than the prey, then the attack and handling step is most important. In this case the prey is easy to find but its size helps it. In most cases such as birds, fish and insects, the central part in foraging is the searching behavior. Foragers in general are either cruise or ambush searchers. Cruiser foragers move continuously and search constantly while ambush searchers sit and wait for prey to come into their strike region. Practically, many species perform a "saltatory search strategy", which is in between the cruise and ambush approaches. In this intermediate strategy, foragers perform all possible search activities. They cruise, ambush and change direction whenever they need either when they stop or while they move. Figure 3.3 shows these foraging search approaches.

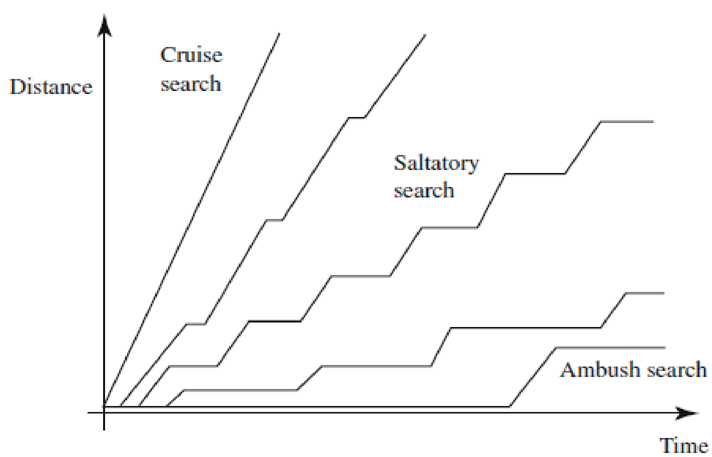

Figure 3.3 Foraging search strategies [234].

As part of their search, some foragers stop and look around to search for prey during the stationary pause between repositioning moves. Repositioning is performed to move the forager into unexplored regions. Scanning and repositioning is illustrated in Figure

3.4 in which a forager is located in the center of a search circle. This circle represents a local scan region. As shown in the figure the forager is assumed to have a pie-shaped search region. The size of the repositioning move taken by the forager is to be optimized in order to enhance the search performance. As demonstrated in the figure, if the move is too large there will be some parts of the search space that are not explored and therefore some opportunities will be missed. On the contrary, if the move is too short, then a large segment of the search space is searched again which is a waste of resources.

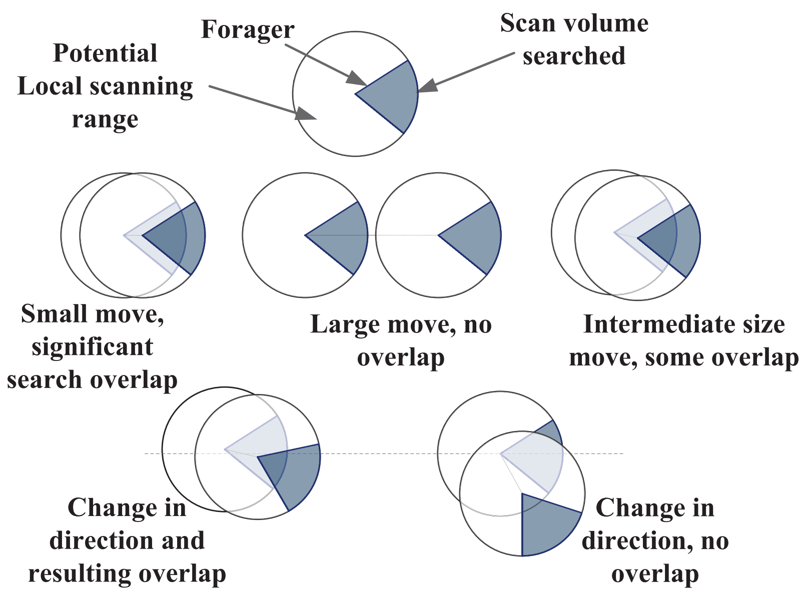

Figure 3.4 Repositioning and scanning trade-off [234].

Based on their scan information, some foragers use the pauses to orient themselves towards prey and change direction accordingly. Obviously, the stop and wait periods are shorter when the prey is large and easy to locate. Searching strategies including repositioning behavior are also highly affected by other factors such as the risk of the encountering predators.

3.5.1.2 Social Foraging

It is natural that animals and organisms live in groups and hence, some kind of social foraging is performed among these groups. Cooperative foraging provides the individuals in a group with effective means for success in their assignments. Sharing information among groups is one of the important features of social foraging. Shared information could be in the form of signals or certain movements or dances or a language in the case of humans. Through social foraging, an individual can obtain higher per capita rate of energetic gain and it can benefit from the information circulated among the group. Grouping can also be helpful in handling large prey and in protecting members from predators in some cases. Natural world examples of cooperative foraging are many such as a pack of wolves, a flock of birds, a school of fish and a colony of ants.

3.5.2 *E. coli* Bacterial Foraging

E. coli bacterium (*Escherichia coli* bacterium) is perhaps the most studied and understood microorganism [235]. It is about 2 µm long and 1 µm wide. An *E. coli* bacterium has a distinctive, capsule shape as shown in Figure 3.5. It has a wall cell with a plasma membrane and an outer wrapper. Inside the cell membrane there is the cytoplasm and nucleoid that form a watery fluid. The cell weighs about 1 picogram and is mainly composed of the cytoplasm which is about 70-percent water. With the appropriate temperature in the environment where the *E. coli* lives (the human gut for example where the temperature is 37ºC) and with enough food it grows and splits into two new copies with all cell parts replicated.

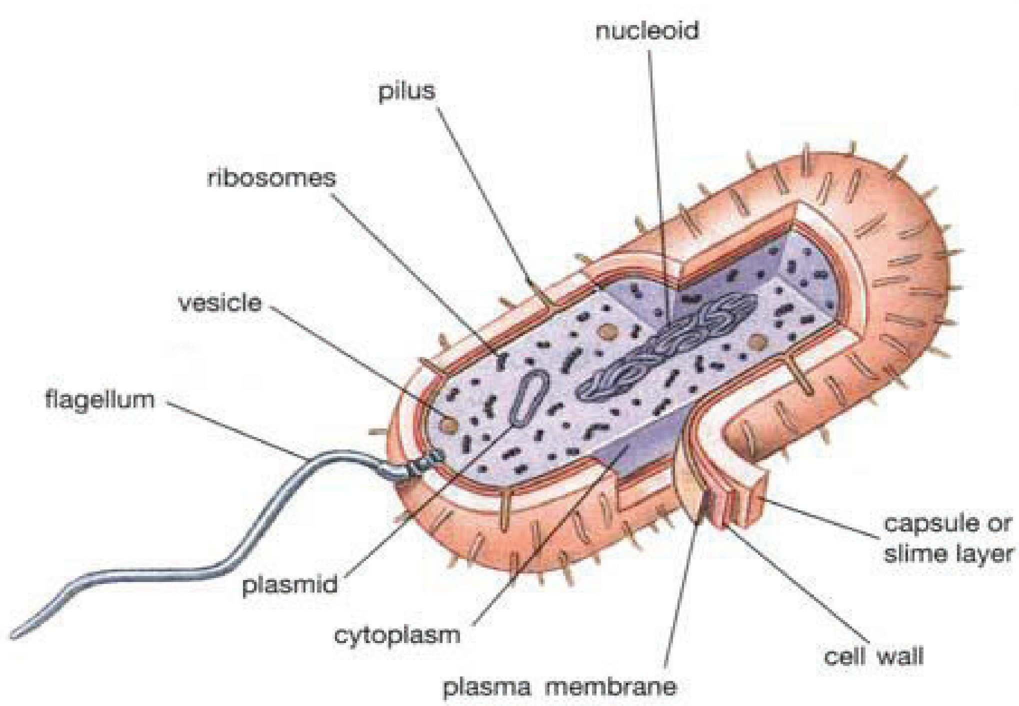

Figure 3.5 *E. coli* bacterium [235]

Locomotion, which is defined as the movement of an organism from one place to another, is performed using the six flagella that *E. coli* bacterium has (only one flagellum is shown in the figure). Various modes of locomotion are executed through a kind of control system which the *E. coli* has and employs to search for nutrient and avoid noxious substances. The motile behavior of the *E. coli* bacteria, which is known as taxes, can be explained with reference to the flagella as an actuator, the decision-making sensors and the closed loop motile behavior which is a kind of saltatory search strategy.

3.5.2.1 Locomotion: Swimming and Tumbling

The *E. coli* bacterium rotates its left-hand flagella in anticlockwise direction simultaneously in order to move and achieve locomotion [236]. This actuating rotation is accomplished at about 100-200 revolutions per second. Each flagellum can be thought of as a kind of propeller that pushes the cell to move it forward. If the rotation is in clockwise direction, then a flagellum will pull at the cell. Figure 3.6 shows what biologists call a "universal joint" and describe as a biological "motor". These terms portray the characteristics of the rotating shaft at the base of the rigid flagellum and the mechanism that enables the flagellum to rotate in either direction relative to the cell. Amazingly, *E. coli* only spends less than 1% of its energy budget on motility as a result of the high efficiency of its biological motor.

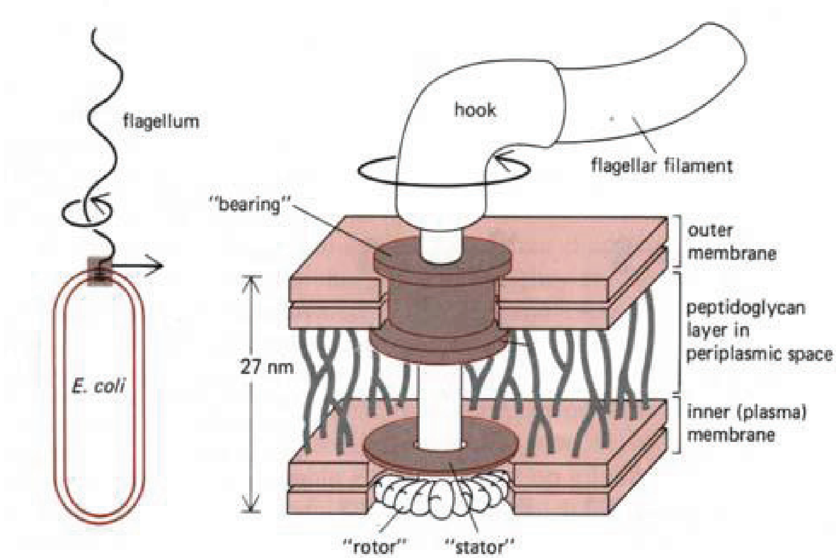

Figure 3.6 *E. coli* bacterium flagellum connection and biological motor [236].

E. coli hardly ever stops rotating its flagella and spends its entire lifetime alternating between two modes of operation; swimming and tumbling. Tumbling results from rotating the flagella clockwise so that each flagellum pulls on the cell independently. When the bacterium tumbles about no direction of movement is set and only a little displacement is experienced. Swimming is the other operation mode that takes place when a bacterium runs for a period of time. Due to its very small size, *E. coli* stops within the diameter of proton without experiencing any inertia but viscosity. This makes tumbling after a run easy and smooth when the cell slows down and stops. Following a tumble interval, the cell will be pointed towards a random direction with a little tendency to be placed in its previous direction in some cases.

3.5.2.2 Chemotaxis: Hill-Climbing

Taxes or chemotaxes is the motility behavior of the bacteria in the presence of chemical attractants and repellents. *E. coli* can be attracted by serine or aspartate while its repellent responses can result from metal ions *Ni* and *Co* in addition to amino acids like leucine and organic acids like acetate.

The basic idea for the behavior of the *E. coli* bacteria as a group is the attempt to search for and locate food avoiding noxious substances. This intelligent-like behavior can be sensed when a group of bacteria is viewed under a microscope. Chemotaxis can be understood in light of the decisions that *E. coli* makes such as how it determines how long to run, when to stop and tumble and how far it swims in the same direction… etc. For instance, when a bacterium is in a neutral environment, where neither food nor noxious substances exist, for a relatively long time, then it alternatively runs and tumbles. Consequently it will move in random directions and hence, it can search for nutrients. In other situations if the bacteria are in a homogeneous and non-gradient concentration of nutrient, then as a result, the run length as well as speed will increase while the tumble periods will decrease. This situation does not guarantee that the *E. coli* will stop searching in spite of the existence of some food. In fact, the search continues for more food. In environments with nutrient gradient, the swimming time is extended while the tumbling time is decreased as long as the bacterium climbs a positive concentration gradient. In contrast, if the bacterium has to swim into noxious substances with a positive gradient or down a nutrient gradient, then it will try to climb back up the concentration gradient or down the noxious one. With these nutrient and noxious gradient changes, the run length and tumbling times are adjusted accordingly. It should be noted; however, that *E. coli* is never satisfied and always searches for richer nutrient concentrations. In such cases when the bacterium happens to be in a concentration of constant nutrient after having been on a positive gradient for some time, it returns, after a short period, to the alternation between swimming and tumbling. Experimental studies showed that the bacterium compares the concentration observed over the past second with those observed in the previous three seconds [237]. Based on this comparison it makes decisions regarding how long to swim [238].

3.5.2.3 Evolution: Reproduction and Elimination/ Dispersion

E. coli bacteria mutate at a rate of about 10^{-7} per gene per generation. In addition, transformation of genes from one bacterium to another occurs through what is called "conjugation". During this activity, gene sequences carry good fitness characteristics as a transmittal of fertility.

Elimination and dispersal events are components of the overall motility of the bacteria. These events could take place as a result of some sudden or gradual changes in environment where a population of bacteria lives. The bacteria are exposed to severe conditions where the population is killed entirely or partially. This could be a result of increases of heat or water floods or any other harsh events. An event could result in dispersal of a bacteria group into another remote part of the environment. Elimination and dispersal events significantly affect the chemotactic process both positively and negatively. They could, for instance, be damaging to the extent that destroys the chemotactic progress. However, they can be beneficial to the chemotactic process as dispersal events may drive bacteria into rich nutrient concentrations.

3.5.3 *E. coli* Bacterial Foraging for Optimization

The bacterial foraging algorithm is a non-gradient stochastic optimization technique. It is non-gradient because it is assumed that no analytical description of the gradient $\nabla J(\theta)$ exists. Inspired by the foraging behavior of the *E. coli* bacteria explained in the previous sections, the BFA is designed to solve non-gradient optimization problems. Suppose that the function be minimized is $J(\theta), \theta \in \Re^p$, where θ represents the position of a bacterium. The function $J(\theta)$ is the resultant effect of attractants and repellents from the environment surrounding the bacterium. The bacterium at position θ is in a nutrient-rich environment when $J(\theta) < 0$, while it is in noxious or neutral environments when $J(\theta) > 0$ or $J(\theta) = 0$ respectively. In light of the bacterial foraging behavior as an optimization process, bacteria always try to find lower values of $J(\theta)$ and avoid getting into positions where $J(\theta) \geq 0$. In other words, they try to climb up nutrient concentrations and avoid being in noxious substances.

To build an *E. coli* bacterial foraging model, a population of bacteria is first defined. After that chemotaxis, reproduction and elimination/ dispersal operations are defined and described. Let j denote the index for the chemotactic step, k is the index for the reproduction step and l is the index for the elimination/ dispersal event. Let the position of each bacterium in the population of the size S at the j^{th} chemotactic step, k^{th} reproduction step, l^{th} elimination/dispersal event is given by:

$$P(j,k,l) = \{\theta^i(j,k,l) \mid i = 1,2,...,S\} \tag{3.19}$$

The cost at the location of the i^{th} bacterium $\theta^i(j,k,l) \in \Re^p$ is denoted as $J(i,j,k,l)$. Referring to J as a cost function (or, as we will use, objective function) is in accordance with the terminology from the optimization literature while the term nutrient surface is in reference to the biological roots of the BFA.

3.5.3.1 Chemotaxis

The number of chemotactic steps that bacteria take during their lifetime is denoted by N_C. The length of steps during the runs is defined as the chemotactic step size and denoted as $C(i) > 0, i = 1,2,...,S$. A tumble is represented by generating a unit length in a random direction $\phi(j)$. In effect, $\phi(j)$ specifies the direction of movement after a tumble. In this random direction, a step is taken with the size $C(i)$ so that the i^{th} bacterium moves to a new position determined by:

$$\theta^i\left(j+1,k,l\right)=\theta^i\left(j,k,l\right)+C(i)\phi(j) \tag{3.20}$$

If the cost $J(i,j+1,k,l)$ at the updated position $\theta^i\left(j+1,k,l\right)$ is lower (better) than $J(i,j,k,l)$ at $\theta^i\left(j,k,l\right)$, then another step is taken in the same direction and same size $C(i)$. This swimming continues as long as the bacterium is doing better by obtaining lower and lower cost. However, there is a maximum number of steps N_S after which swimming stops.

3.5.3.2 Swarming

The cost function of each bacterium in the population is affected by a kind of swarming that is performed by the cell-to-cell signaling released by the bacteria groups to form swarm patterns. The cell-to-cell signaling for the i^{th} bacterium is represented by $J_{CC}^i(\theta,\theta^i(j,k,l)), i=1,2,\ldots S$. The depth of the attractant released by the cell is denoted by $d_{attract}$ and the width of the attractant signal is measured as $w_{attract}$. On the other hand, a repellent signals are also released by the cell with the height of this repellent effect $h_{repellent}=d_{attract}$ and width $w_{repellent}$. The combined cell-to-cell attraction and repelling effects are expressed as:

$$\begin{aligned}
J_{CC}\left(\theta,P(j,k,l)\right) &= \sum_{i=1}^{S} J_{CC}^i\left(\theta,\theta^i(j,k,l)\right) \\
&= \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] \\
&\quad+\sum_{i=1}^{S}\left[h_{repellant}\exp\left(-\omega_{repellant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right]
\end{aligned} \tag{3.21}$$

were $\theta=[\theta_1,\theta_2,\ldots\theta_p]^{\mathrm{T}}$ is points on the optimization domain and θ_m^i is the m^{th} component of the i^{th} bacterium position θ^i. The cost is now defined as $J(i,j,k,l)+J_{CC}(\theta,P)$ instead of $J(i,j,k,l)$. This cost describes the swarming effect produced by the members of the population. Consequently, bacteria try to move towards each other, but not too close while searching for nutrients and trying to avoid noxious substances at the same time.

3.5.3.3 Reproduction and Elimination/Dispersal Events

A reproduction step is taken after executing the maximum number of chemotactic steps N_C. The number of reproduction steps to be taken is defined as N_{re}. A successful member of the population who has obtained sufficient nutrients during its lifetime reproduces and splits into two cells with no mutation. The number of these successful members is given by (assuming, for convenience, that S is a positive even integer):

$$S_r = \frac{S}{2} \tag{3.22}$$

To perform the reproduction task, the population is sorted in ascending order of accumulated cost. The unhealthy member that did not obtain as many nutrients during its lifetime is unlikely to produce. While the healthiest half of the population reproduce and split each into two, the other S_r least healthy bacteria die as a consequence. This course of action will keep the population size constant which is suitable for algorithm coding.

The number of elimination and dispersal events is denoted by N_{ed}. Each bacterium in the population is subjected to elimination/dispersal with probability p_{ed} when an event takes place. Elimination and dispersal events are assumed to occur less frequently than reproduction steps. A bacterium takes many chemotactic steps before reproduction while it may experience an elimination/ dispersal event after a number of generations take place.

3.5.3.4 Basic Bacterial Foraging Algorithm

The various parameters that have been mentioned above must be primarily set in order to initialize the execution of the algorithm. Initial values must be chosen for p, S, N_C, N_S, N_{re}, N_{ed}, p_{ed} and $C(i), i = 1,2,...,S$. In addition, the parameters of the cell-to cell functions have to be chosen if swarming is brought into play. Initial solution points, represented by the initial positions for the members of the population, must be specified. Principally, initial values could be randomly distributed throughout the search hyper space. A good choice for these initial values is to locate them in the visible region where the optimal solution could exist. Initially, the indexes for the chemotactic step, the reproduction step and the elimination/ dispersal event are all zeroed ($j = k = l = 0$). It should be obviously noted that P is automatically updated as a result of updating θ^i . The basic BFA details are as follows [232]:

1. Initialization of the parameters
2. Elimination/ dispersal loop: l=l+1
3. Reproduction loop: k=k+1
4. Chemotaxis loop: j=j+1

(a) For $i = 1,2,...,S$, a chemotactic step to be taken by the i^{th} bacterium

(b) Compute $J(i, j, k, l)$

$$J(i, j, k, l) = J(i, j, k, l) + J_{CC}(\theta, P) \tag{3.23}$$

(This adds on the cell-to cell attraction effect to the nutrient concentration)

(c) Let $J_{last} = J(i, j, k, l)$ to save this value, since better cost may be found via a run

(d) Tumble: generate a random vector $\Delta(i) \in \Re^p$ with each element $\Delta_m(i), m = 1,2,..., p$, a random number on $[-1,1]$.

(e) Move: let

$$\theta^i\left(j+1, k, l\right) = \theta^i\left(j, k, l\right) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{3.24}$$

This results in a step of size $C(i)$ in the direction of the tumble for bacterium i .

(f) Compute $J(i, j+1, k, l)$ and let

$$J(i, j+1, k, l) = J(i, j+1, k, l) + J_{CC}(\theta^i(j+1, k, l), P(j+1, k, l)) \tag{3.25}$$

(g) Swim:

- Let $m = 0$ (counter for swim length).
- While $m < N_S$ (if have not climbed down too long)
  - Let $m = m + 1$.

- If $J(i,j+1,k,l) < J_{last}$ let $J_{last} = J(i,j+1,k,l)$ and let

$$\theta^i\left(j+1,k,l\right) = \theta^i\left(j+1,k,l\right) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{3.26}$$

and use this $\theta^i\left(j+1,k,l\right)$ to compute the new $J(i,j+1,k,l)$ the same way shown in *(f)* above.

- Else, let $m = N_S$. The end of the while statement.

(h) Go to next bacterium $(i+1)$ if $i \neq S$ (i.e., go to *(b)* above to process the next bacterium).

5. If $j < N_C$, go to step 4. In this case, continue chemotaxis, since the life of the bacteria is not over.
6. Reproduction:

   (a) For the given k and l, and for each $i = 1,2,...,S$, let

$$J^i_{health} = \sum_{j=1}^{N_C+1} J(i,j,k,l) \tag{3.27}$$

   be the health of bacterium i (a measure of how many nutrients it got over its lifetime and how successful it was at avoiding noxious substances). Sort bacteria and chemotactic parameters $C(i)$ in order of ascending cost J_{health} (higher cost means lower health).

   (b) The S_r bacteria with the highest J_{health} values die and the other S_r bacteria with the best values split (and the copies that are made are placed at the same location as their mother).

7. If $k < N_{re}$, go to step 3. In this case, the number of specified reproduction steps has not been reached, so the next generation in the chemotactic loop is started.
8. Elimination/ dispersal: for $i = 1,2,...,S$, with probability p_{ed}, eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant). To do this, if you eliminate a bacterium, simply disperse one to a random location on the optimization domain.
9. If $l < N_{ed}$, then go to step 2; otherwise end.

The fundamental BFA methodology is summarized in the flowchart of Figure 3.7.

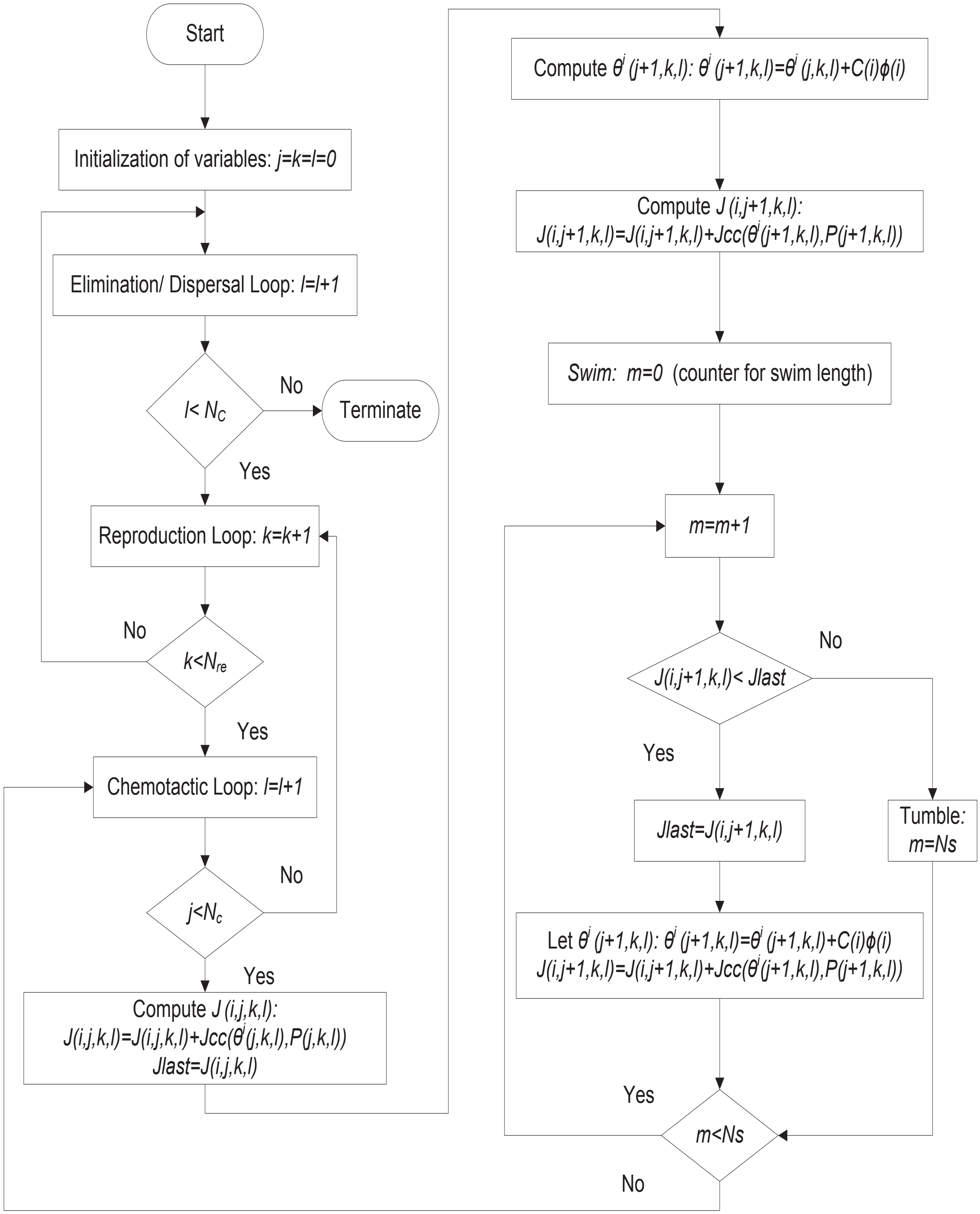

Figure 3.7 Basic BFA for optimization

3.5.3.5 Algorithm Parameter Tuning

As shown in the previous section, the BFA uses a number of parameters that need to be appropriately tuned. The size of the population S , for instance, can significantly affect the computational requirements of the algorithm. Although a large population guarantees that initial points are more likely located near optima but, the computational complexity will increase by increasing the size of the population. The chemotactic step size $C(i)$ should be chosen to fit the nature of the problem. Too large a step makes the algorithm overlook local minima by swimming without stopping at them especially when the minimum point is located in a valley with steep edges. On the other hand, too small values of step size can make the convergence very slow.

Large values of the number of chemotactic steps N_C , reproduction steps N_{re} and elimination/ dispersal events N_{ed} will result in more complex computations although that will also lead to better optimization progress. If N_C , for example, is too small then the algorithm will rely more on reproduction besides luck. Moreover, it could more likely get trapped in local minima. Similarly, if the value of N_{re} is too small, the algorithm could experience a premature convergence. N_{re} , plays an influential role in focusing on good regions and ignoring bad ones. Large values of N_{ed} help the algorithm find favorable regions and look in other parts of the search space.

Example 3.1 [232]**:**

This example is designed to illustrate the performance of the BFA to find the minimum of the function shown in Figure 3.8. In the figure, the nutrient landscape, which is the optimization domain, is shown with optimum points are represented by valleys. These valleys are nutrient rich concentrations while noxious substances are represented by peaks. The global minimum for this function is the point $[15, 5]^T$.

The algorithm parameters are chosen as $S = 50$, $N_C = 100$, $N_S = 4$, $N_{re} = 4$, $N_{ed} = 2$, $p_{ed} = 0.25$ and $C(i) = 0.1, i = 1, 2, ..., S$. The initial positions of the bacteria are randomly distributed all over the search space.

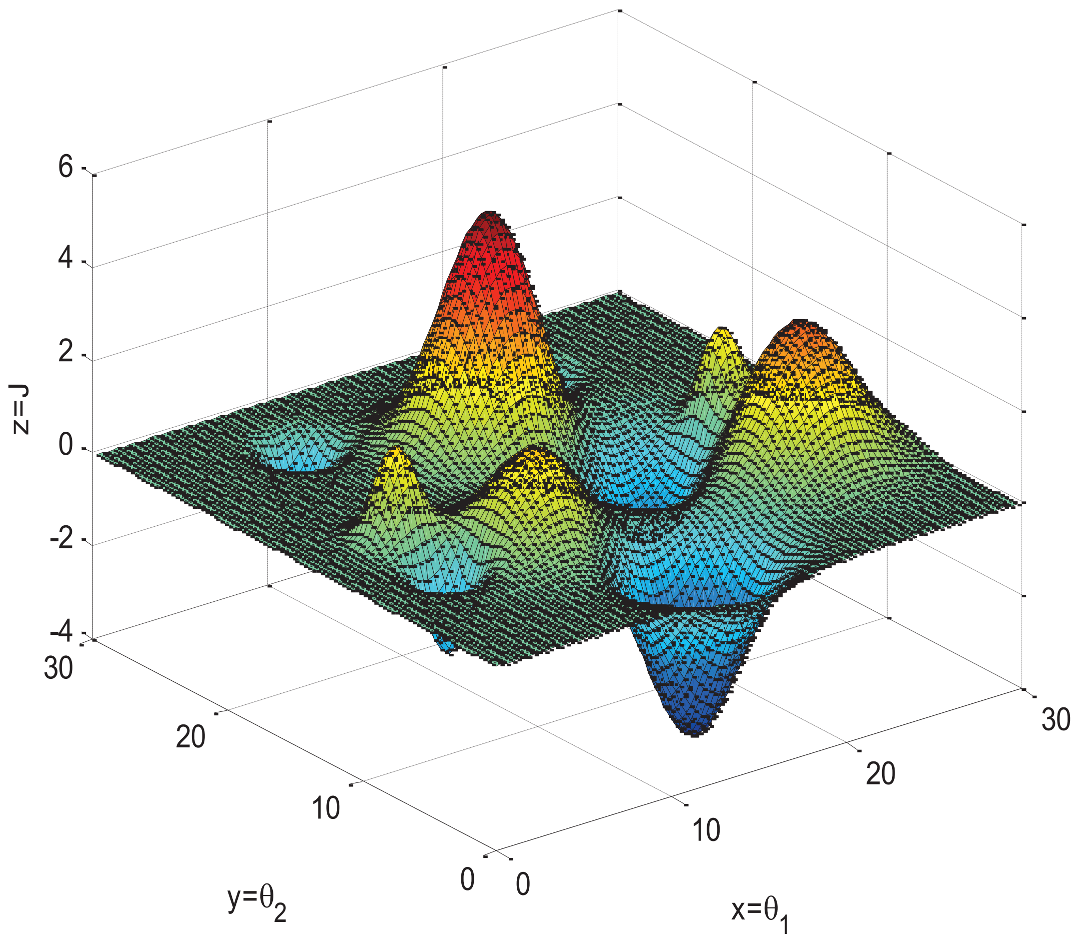

Figure 3.8 Optimization domain of the function in Example 3.1

The motion trajectories of the bacteria are shown in Figure 3.9. The first generation started from their initial random positions. It is shown in the figure that the bacteria try to avoid peak points and pursue the valleys. In the second generation when reproduction takes place, the 25 healthiest bacteria are reproduced. The reproduction occurs again in the third and fourth generations.

In Figure 3.10, an elimination/dispersal event takes place and other four generations perform the chemotactic and reproduction steps. It can be seen that the location of some bacteria is displaced to explore other parts of the search space.

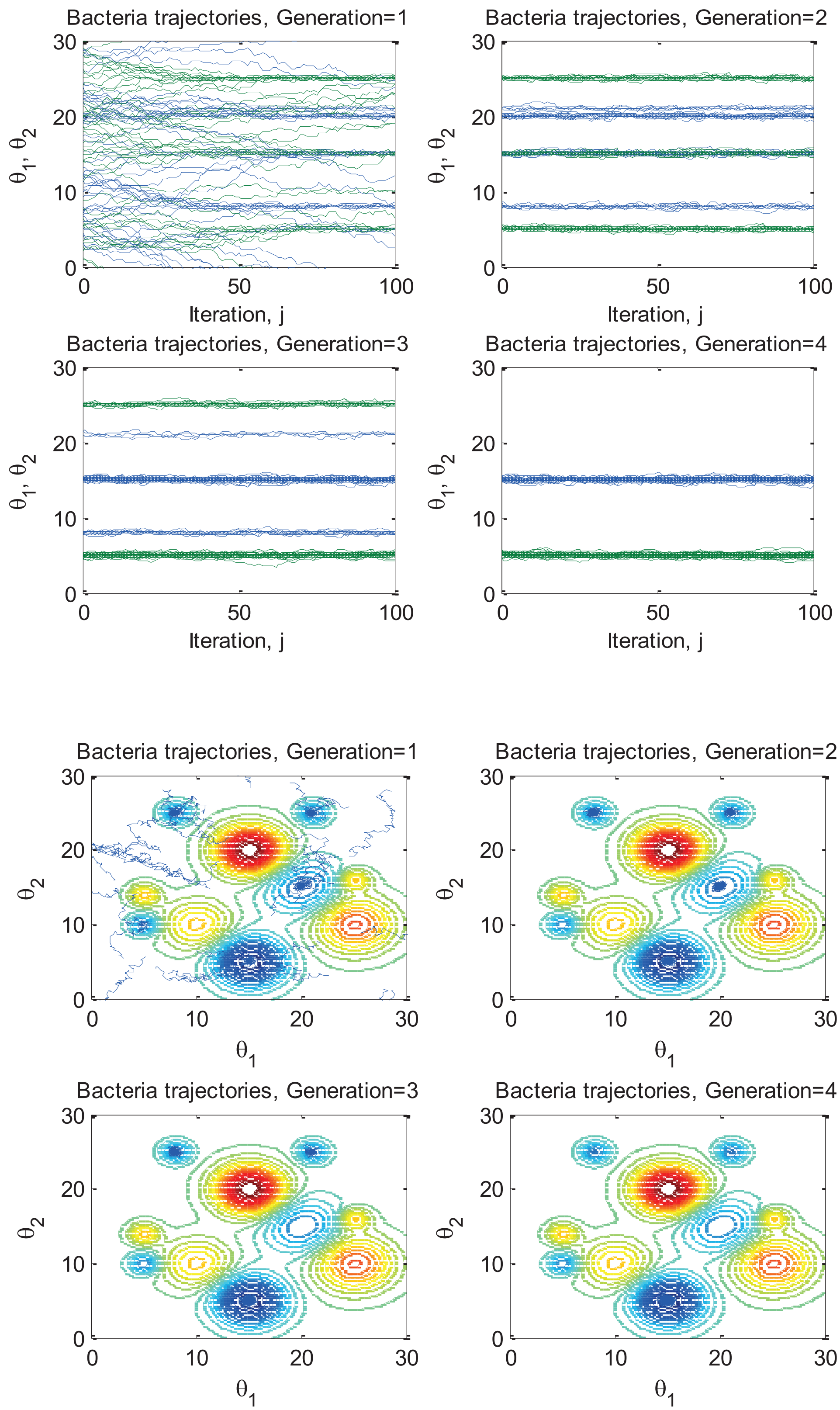

Figure 3.9 Bacterial motion, generations 1-4

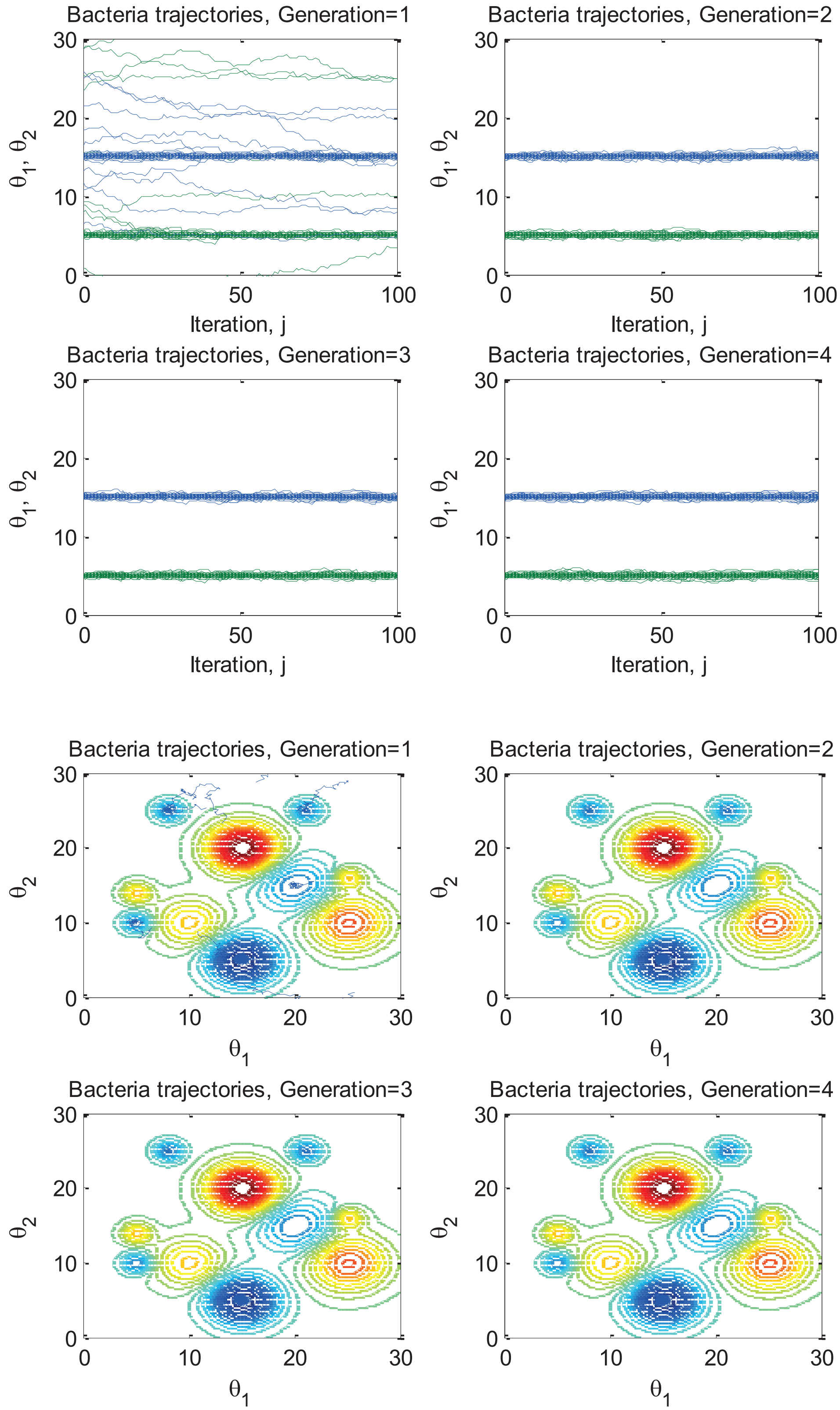

Figure 3.10 Bacterial motion, generations 1-4, after an elimination/dispersal event

3.6 PROPOSED MODIFIED BACTERIAL FORAGING ALGORITHM

As demonstrated in Example 3.1, BFA has been successfully used to solve unconstrained small scale optimization problems. However, simulation results revealed that the BFA suffers from poor convergence properties and high computational requirements. This poor behavior gets worse in dynamic environments and high dimension search spaces associated with complex problems. In addition to the simulation results obtained throughout the research efforts conducted in this thesis, the deficiency of the basic BFA performance has commonly been reported in the literature [239, 240]. Consequently, important and critical adjustments are required to enhance the performance of the algorithm and deal with the complexity and high-dimensioned search space of constrained large-scale problems. In this work, two major modifications are introduced to the original BFA. Firstly, the basic chemotactic step is adjusted to have a dynamic behavior in order to improve balancing the global and local search. Secondly, the stopping criterion is adapted to fluctuate according to the solution improvement instead of the preset maximum number of iterations.

3.6.1 Adaptive Dynamic Run-Length Unit for Chemotaxis

The run-length unit, which is the chemotactic step size $C(i)$, of the basic BFA is a constant parameter that could guarantee good searching results for small optimization problems. However, as mentioned earlier, when applied to complex constrained large-scale problems with high dimensionality it shows poor performance. The run-length parameter is the key factor for controlling the local and global search ability of the BFA. From this perspective, balancing the exploration and exploitation of the search could be achieved by adjusting the run-length unit. If the size of the chemotactic step is too large, the bacteria will explore the search space in a wide-ranging manner. On the other hand if the size is too short, the search will be limited to local small areas. It should be mentioned that several dynamic functions are implemented in other evolutionary algorithms to control the local and global search ability of the algorithm [241-243]. In this thesis, two adaptive dynamic functions are proposed and applied instead of the preset constant step.

The first is a linearly decreasing dynamic function and the second is a nonlinear function. The two functions are respectively expressed as follows:

$$C(i,j) = C(N_C) + \left(C(1) - C(N_C)\right)\left(\frac{N_C - j}{N_C}\right) \tag{3.28}$$

$$C(i,j+1) = \left(\frac{C(i,j) - C(N_C)}{N_C + C(N_C)}\right)\left(N_C - j\right) \tag{3.29}$$

where j is the chemotactic step index and N_C is the maximum number of chemotactic steps while $C(1)$ and $C(N_C)$ are initial predefined parameters.

3.6.2 Adaptive Stopping Criterion

The stopping criterion of the original BFA is the predefined maximum number of chemotactic steps, reproduction steps and elimination/dispersal events. This criterion increases the computation requirements of the algorithm in some cases. In this work, an adaptive stopping criterion is applied so that the algorithm adjusts the maximum number of iterations depending on the improvement of the cost function. The chemotaxis operation stops either when there is no further improvement in the solution after a certain number of iterations or when the maximum number of chemotactic steps is reached.

3.7 CONSTRAINT HANDLING

A constrained optimization problem can have inequality or equality constraints or both as discussed in Section 3.2 earlier. An inequality constraint is violated when a bacterium swims out of the search space boundaries. In this case the corresponding entry in the bacteria position vector is relocated into its immediate previous feasible position. This, in fact, is the principle of rejecting the infeasible solutions and preserving the feasible ones [244]. Such procedure is performed so as to maintain the randomness and stochastic features of the algorithm while keeping each bacterium in active mode instead of applying the death penalty, even if it moves out of the boundaries.

The objective function is augmented by the equality constraints using penalty factors. The resulting equation is called the evaluation function (F_{eval}). In the proposed algorithm, the penalty function utilized is formulated as a dynamic nonlinear increasing function [245-247]. The proposed evaluation function that would be computed in each iteration is mathematically expressed as follows:

$$F_{eval} = F_T + (A \times j)^y \sum_{i=1}^{m} f_i^{\,z} \tag{3.30}$$

The parameters A , y and z are constants, j is the index for the chemotactic step and m is the number of equality constraints. The set of functions $f_i\,(1 \le i \le m)$ construct the penalty term so that the function f_i measures the violation of the i^{th} equality constraint. The violation function f_i is computed as follows:

$$f_i = | g_i(x) | \tag{3.31}$$

The function $g_i(x)$ represents the i^{th} equality constraint in accordance to Equation (3.2). The formulation of Equation (3.30) shows that the first part of the penalty function, $(A \times j)^y$ grows larger as the number of iterations increases.

To demonstrate the effectiveness and the good performance of the proposed MBFA, it is applied to solve several optimization problems. The following examples are selected to show the significant input of the proposed modifications as well as the efficiency of the constraint-handling scheme. The proposed algorithm is implemented in MATLAB 7.8 and executed on an Intel Core 2 Duo 1.66 GHz personal computer. In each test case, 50 independent runs were conducted with different random initial solution for each run.

Example 3.2:

In this example the proposed MBFA is employed to find the global solution to the following minimization problem [231]:

$$F(x_1,x_2) = x_1 - x_2 - 5\sin(2x_1 + x_2) - \cos(3x_1 - x_2) + \sin(x_1 - x_2) - \cos(x_1 + x_2) \tag{3.32}$$

subject to $\quad -5 \le x_1, x_2 \le 5 \qquad (3.33)$

The function to be minimized is shown in Figure 3.11. The function has multiple peaks and valleys. Minimization of this function is a real challenge for any optimization technique although it is much easier for heuristic methods to find the global minimum.

The existence of multiple local maxima and minima makes derivative-based deterministic methods most likely get trapped in these local optima unless the initial solution was luckily located near the global minimum.

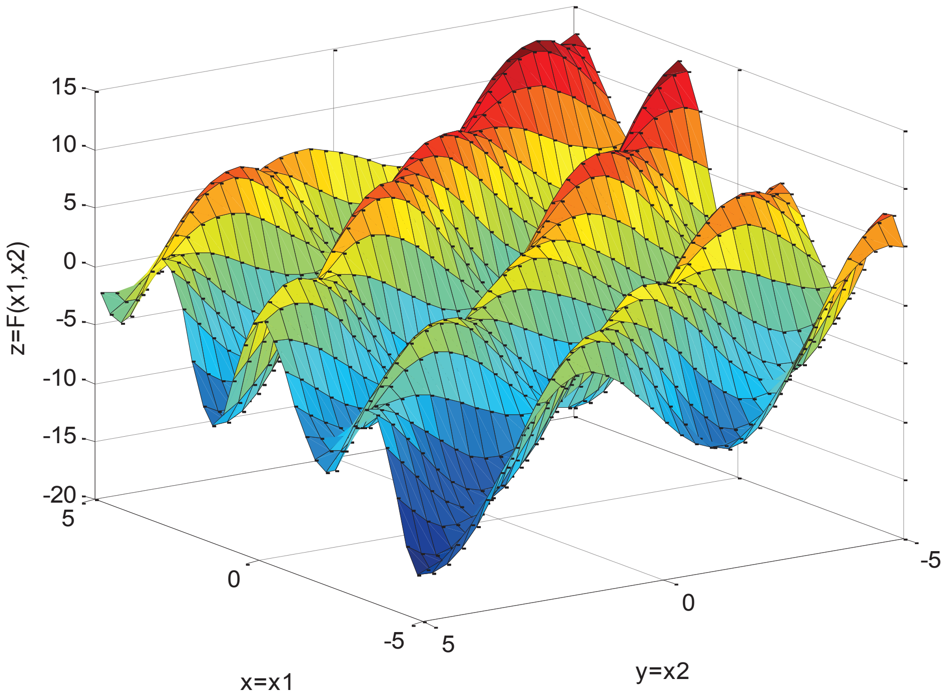

Figure 3.11 Multi local optima function of Example 3.2

The parameters of the algorithm are chosen as $S = 10$, $N_C = 50$, $N_S = 10$, $N_{re} = 4$, $N_{ed} = 2$, $p_{ed} = 0.25$, $C(1) = 1$ and $C(N_C) = 0.0001$. In order to appropriately tune the parameters the algorithm was run many times before finally the parameters were selected. The proposed MBFA was executed 50 independent runs to proof its effectiveness and robustness. In each run, the initial solutions were randomly distributed to maintain the stochastic features of the algorithm as a heuristic approach. The results, as shown in Table 3.1, reflect the capability of the proposed BFA to find a very near global solution.

Table 3.1 Results for Example 3.2

Solution		Objective			Average time (sec)
x_1	x_2	Min	Max	Average	
-4.7124	4.7124	-16.4249	-16.4224	-16.4248	0.0702426

The performance of the proposed MBFA is illustrated in Figure 3.12, Figure 3.13 and Figure 3.14. The first two figures show the bacterial trajectories for the four generations in their search for the global minimum before and after the occurrence of the elimination/ dispersal event. Figure 3.14 shows the objective function improvement by the increase of the chemotactic steps during the reproduction and elimination/ dispersal events.

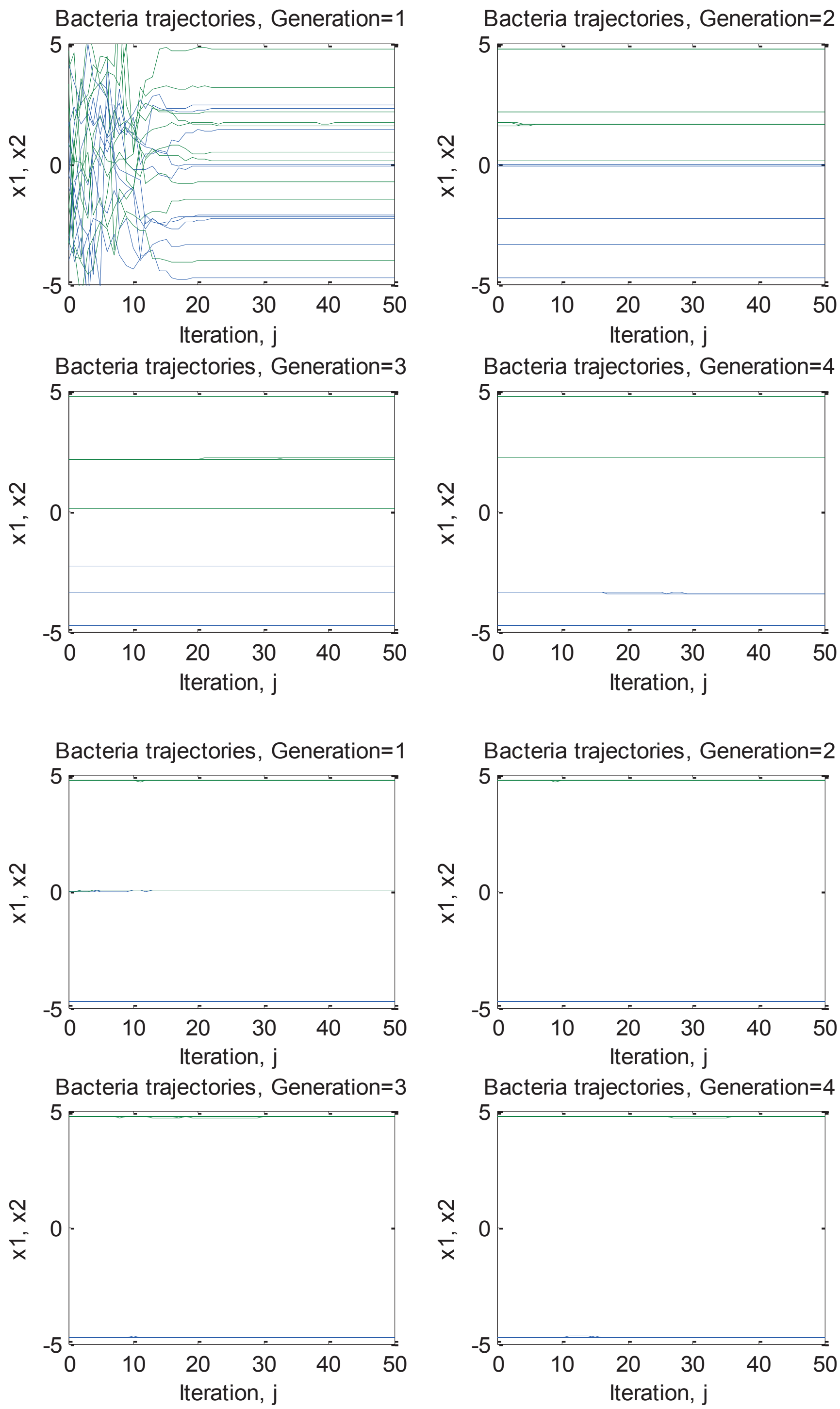

Figure 3.12 Bacterial motion trajectories for Example 3.2
(2 elimination/dispersal events)

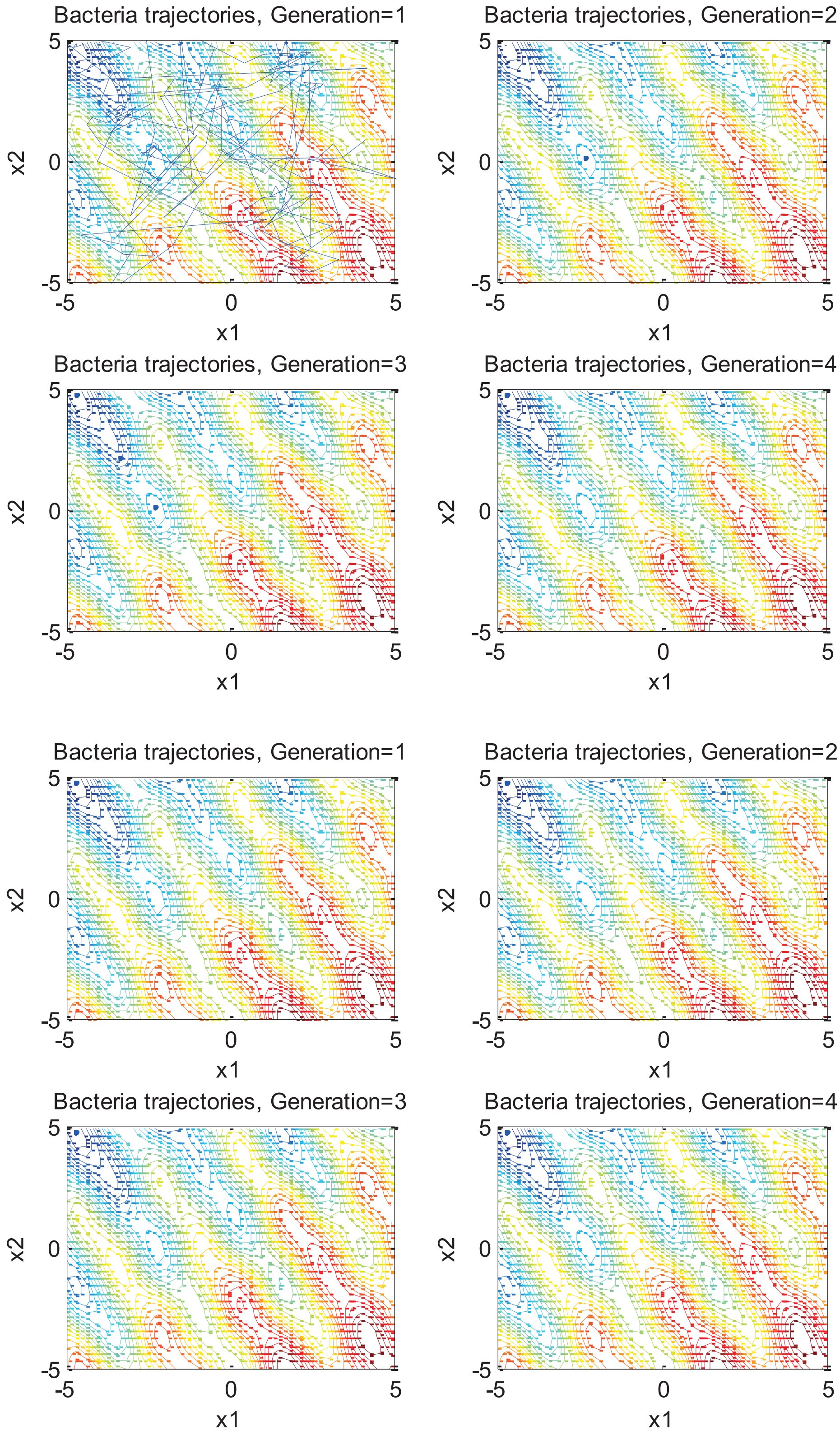

Figure 3.13 Motion trajectories on contour plots for Example 3.2
(2 elimination/dispersal events)

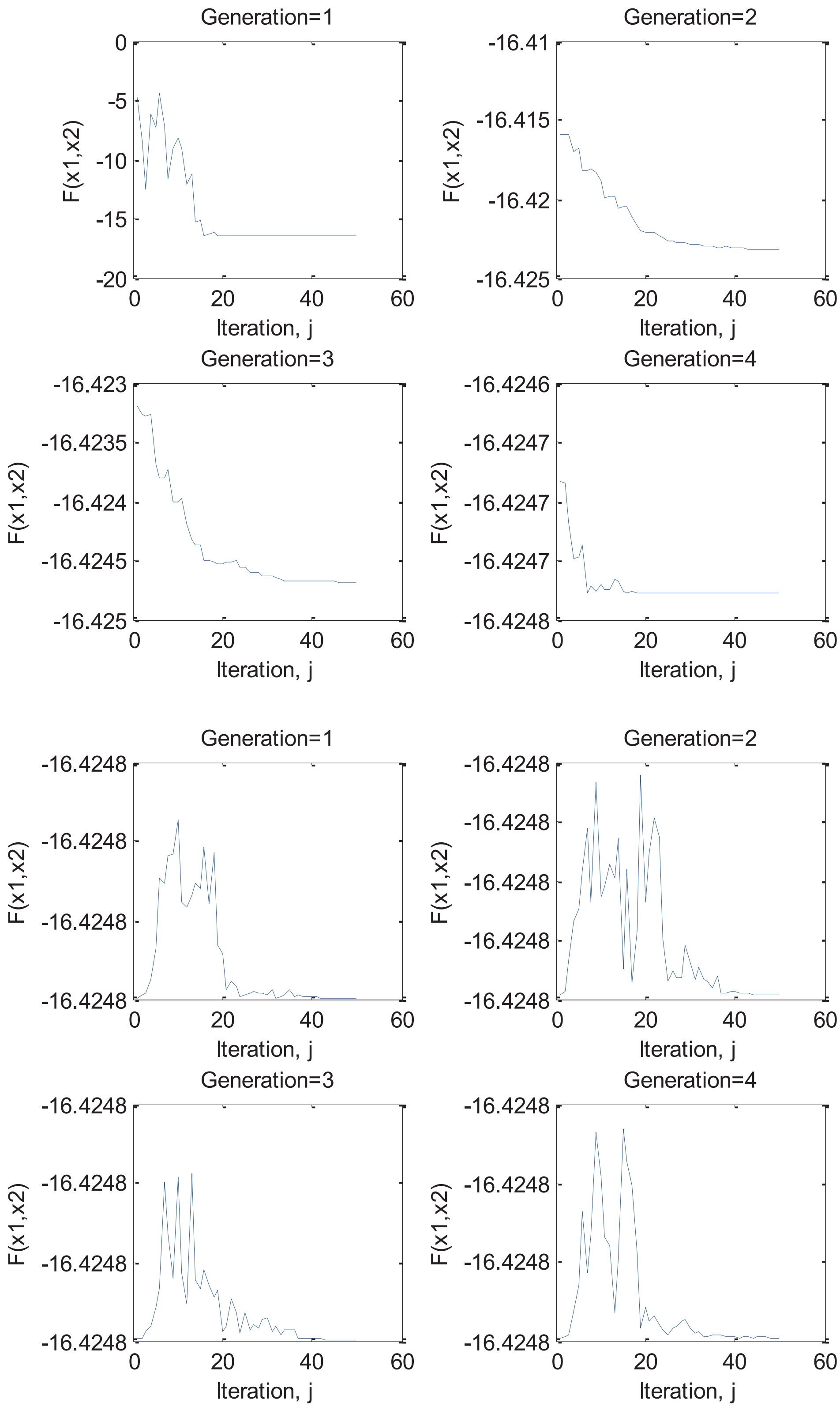

Figure 3.14 Objective function vs. iteration number for Example 3.2

Example 3.3:

In this example, the function to be minimized is the Rosenbrock's banana function. The global minimum is known to be $f(x_1^*, x_2^*, \ldots, x_n^*) = 0$ which occurs at $(1,1,\ldots,1)$. This function is a standard test function and it is a quite tough for almost all of the optimization algorithms. This difficulty in finding the global optimum of this function is obvious because of the non-convex characteristics that are shown in Figure 3.15 for the two-dimensioned function. However, using the MBFA, the global minimum could be easily found. The optimization function to be minimized is:

$$F(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n-1} [(1 - x_i)^2 + 100(x_i^2 - x_{i+1})^2] \tag{3.34}$$

subject to $\quad -50 \le x_1, x_2, \ldots, x_n \le 50 \quad$ (3.35)

The problem space dimension n is chosen as $n = 100$ to demonstrate the ability of the MBFA to perform effectively in finding the global, or close to global, minimum for problems with high dimension search spaces. The parameters of the algorithm are tuned to the same values in Example 3.1 except for the maximum number of swimming steps in the same direction which is chosen to be $N_S = 20$.

The MBFA is applied and successfully implemented to solve this optimization problem and find the global optimal, or near to optimal, solution. The number of runs executed in this problem is 50. Results obtained are listed in Table 3.2.

Table 3.2 Results for Example 3.3(n=100)

Solution	Objective			Average time (sec)
$x_1, x_2, \ldots, x_n$	Min	Max	Average	
1.0000	1.7251e-10	2.02246e-09	8.2324e-10	0.1664537

In order to visualize the characteristics of the Rosenbrock's banana function, the MBFA is applied to solve this problem considering the two-dimension form of the function. The non-convex characteristics and the smooth parabolic valley of the function are plotted in Figure 3.15. The function in two-dimension space is expressed as follows:

$$F(x_1, x_2) = (1 - x_1)^2 + 100(x_2 - x_1^2)^2 \tag{3.36}$$

subject to $$-10 \le x_1, x_2 \le 10 \tag{3.37}$$

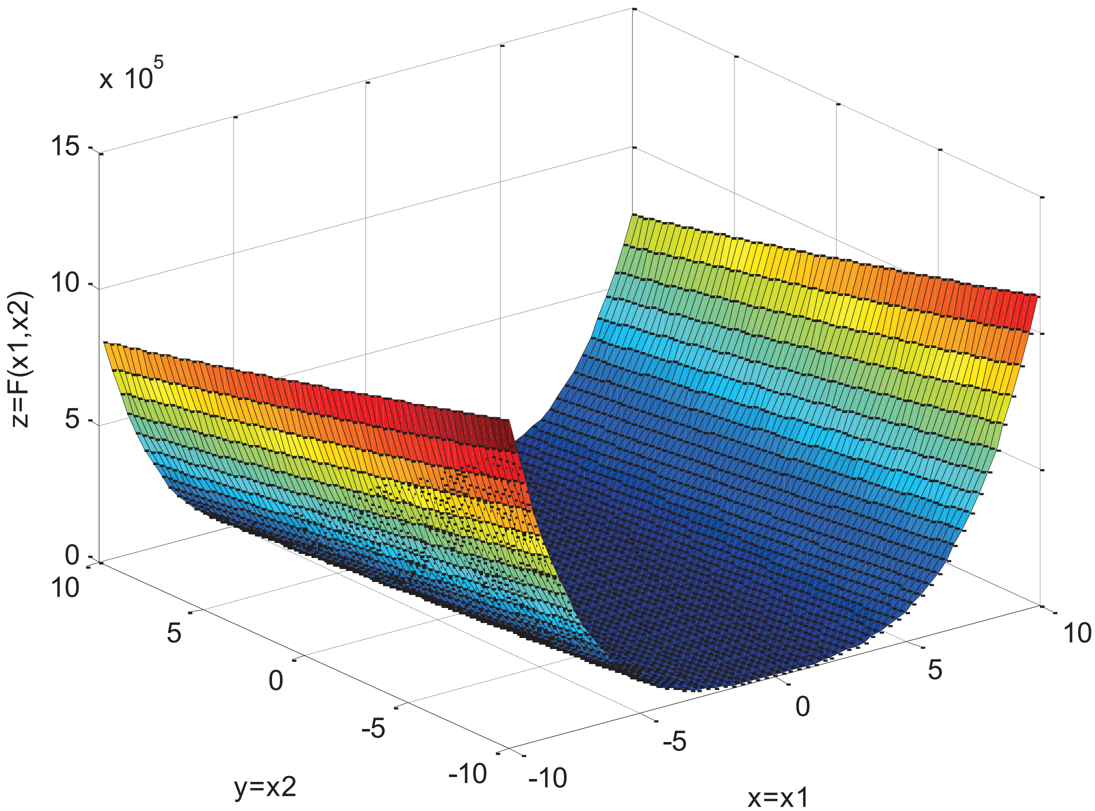

Figure 3.15 Rosenbrock's banana function of Example 3.3 (n=2)

The parameters of the algorithm are kept unchanged as above and the results obtained are listed in Table 3.3 while the performance of the algorithm is shown by Figure 3.16, Figure 3.17 and Figure 3.18.

Table 3.3 Results for Example 3.3 (n=2)

Solution		Objective			Average time (sec)
x_1	x_2	Min	Max	Average	
1.0000	1.0000	3.4271e-13	7.2145e-12	6.3286e-13	0.0942482

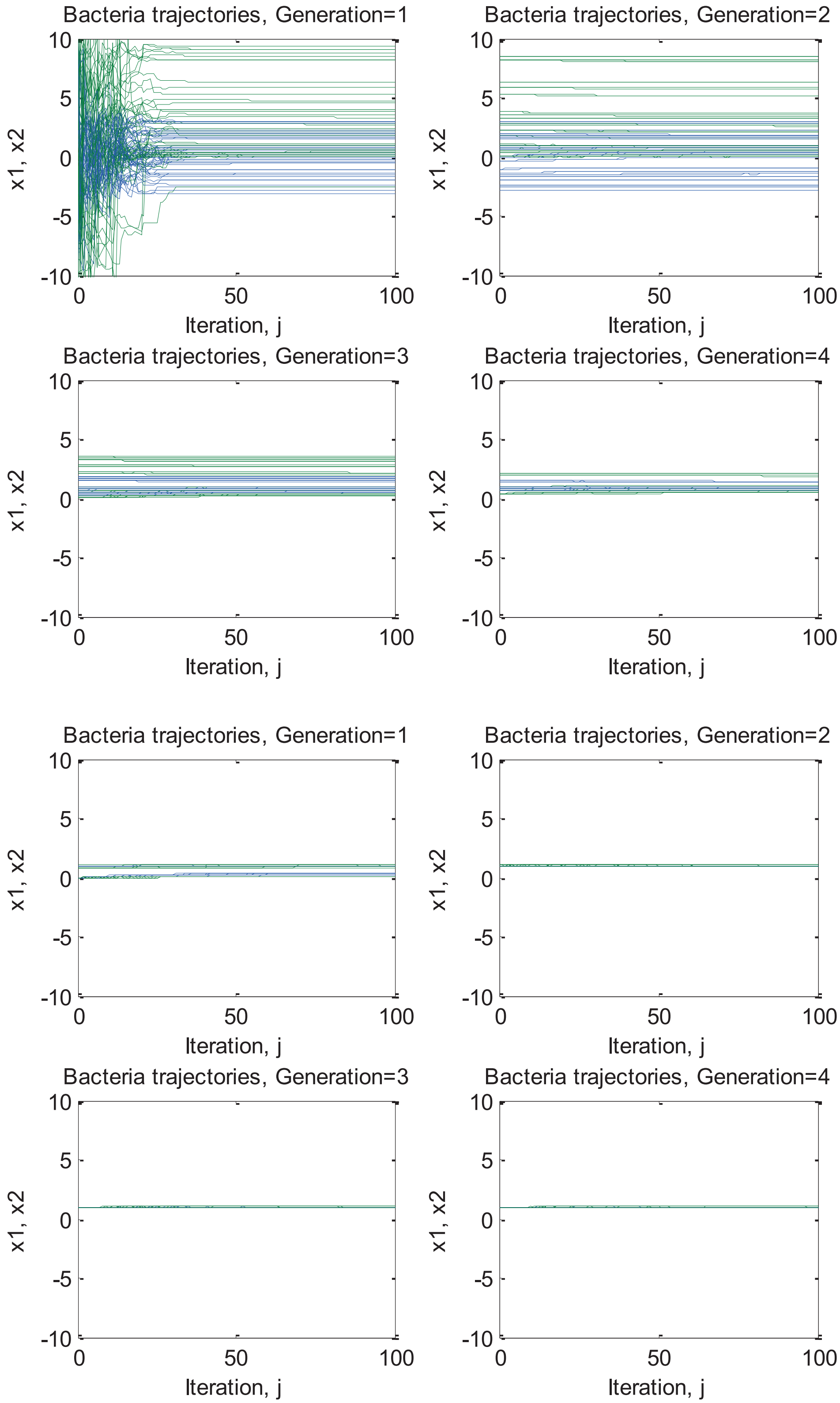

Figure 3.16 Bacterial motion trajectories for Example 3.3

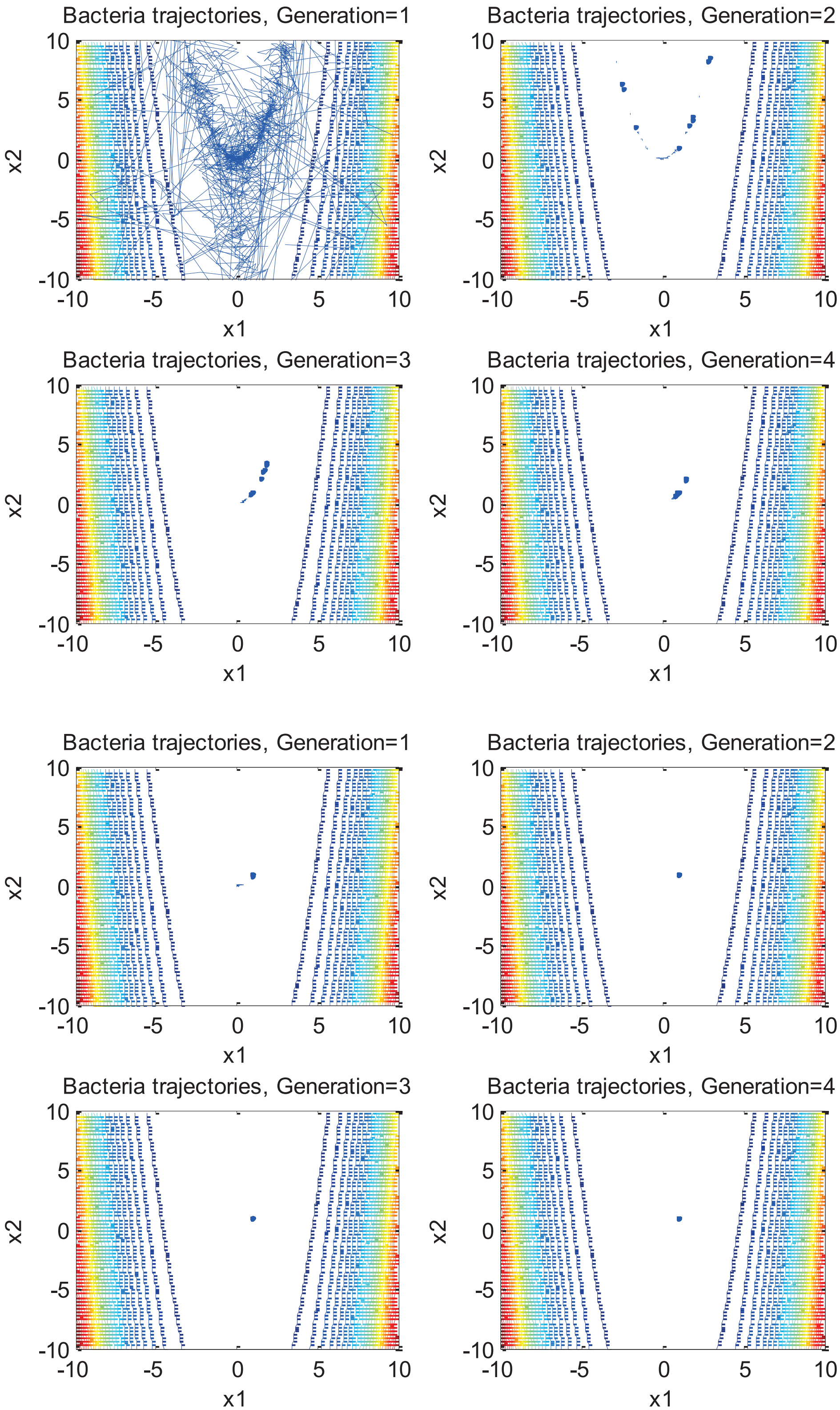

Figure 3.17 Motion trajectories on contour plots for Example 3.3

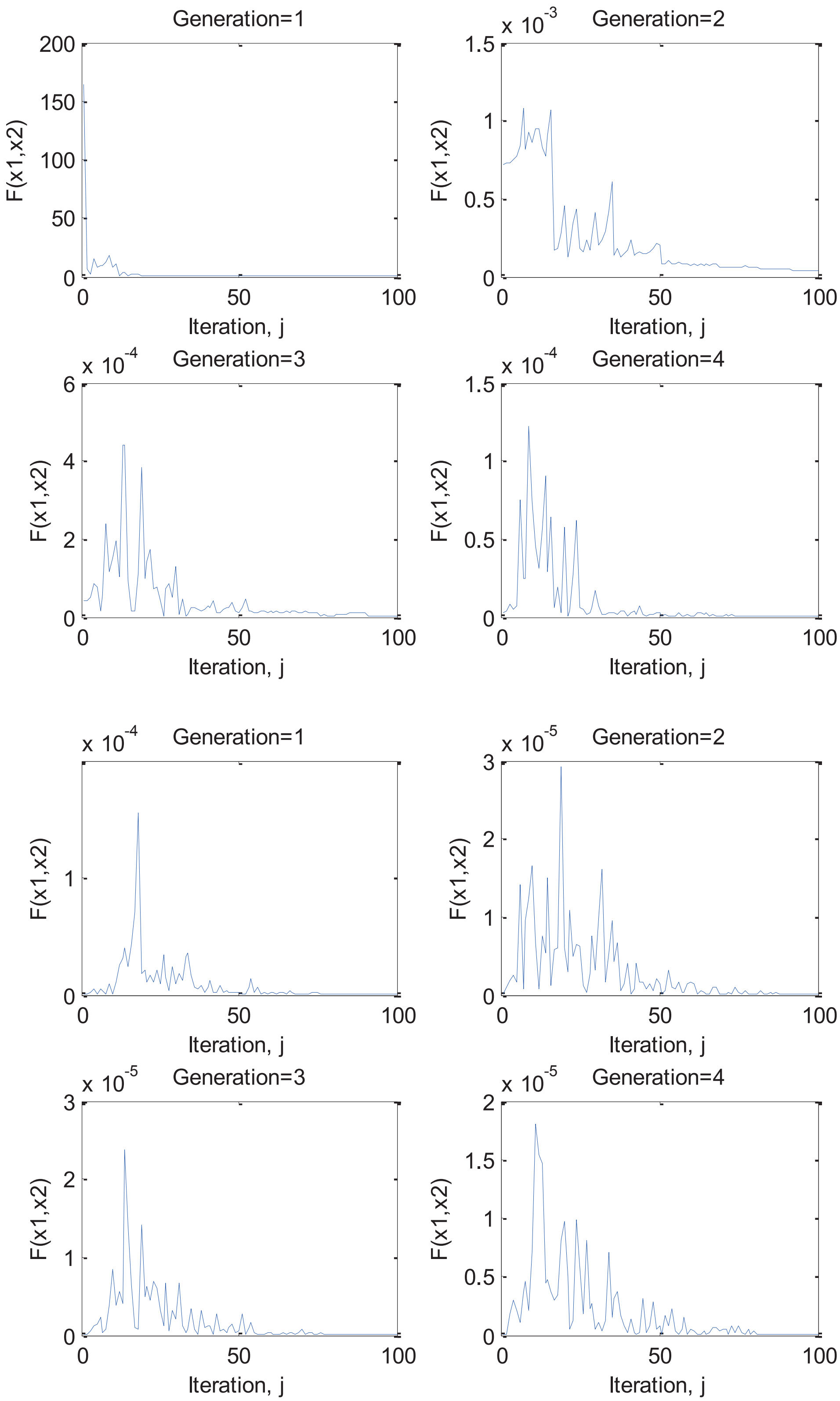

Figure 3.18 Objective function vs. iteration number for Example 3.3

Example 3.4:

A more complicated function is used in this example to demonstrate the effectiveness of the MBFA. In this example, the function to be minimized is known as the egg crate function which is shown in Figure 3.19.

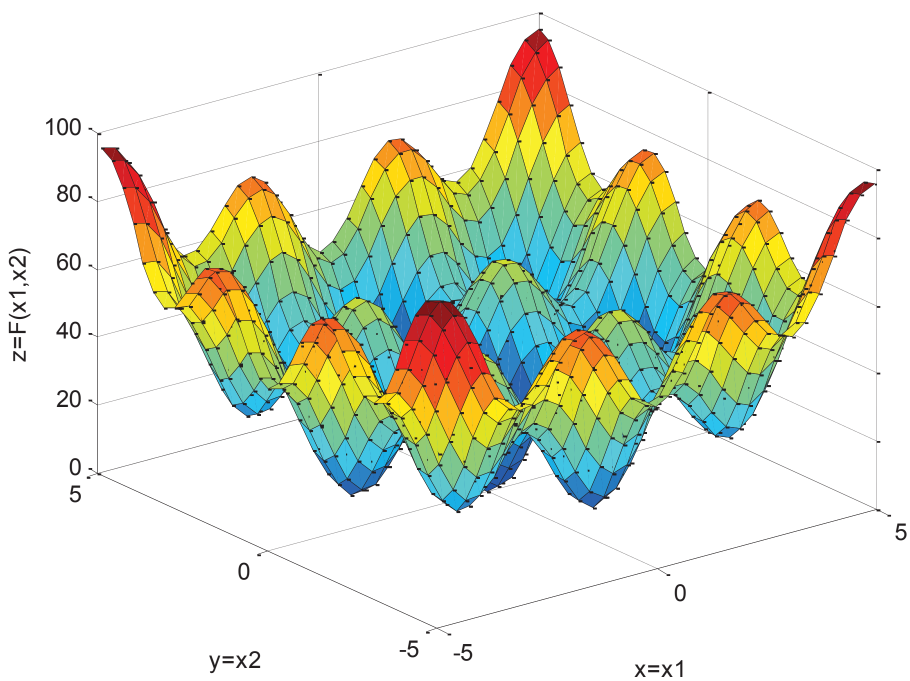

Figure 3.19 Egg crate function for Example 3.4

The objective function to be minimized is given as:

$$F(x_1, x_2) = x_1^2 + x_2^2 + 25[\sin^2(x_1) + \sin^2(x_2)] \tag{3.38}$$

subject to $-5 \le x_1, x_2 \le 5$ (3.39)

The egg crate function is known to have global minimum $f(x_1^*, x_2^*) = 0$ at $(0,0)$. Applying the MBFA with the same parameters used in Example 3.2, the solution point and the minimized function are shown in Table 3.4. The paths trajectories of the bacteria are shown in Figure 3.20, Figure 3.21 and Figure 3.22.

Table 3.4 Results for Example 3.4

Solution		Objective			Average time (sec)
x_1	x_2	Min	Max	Average	
4.4e-07	-1.0425e-08	1.7167e-011	1.1863e-010	3.3551e-011	0.0869911

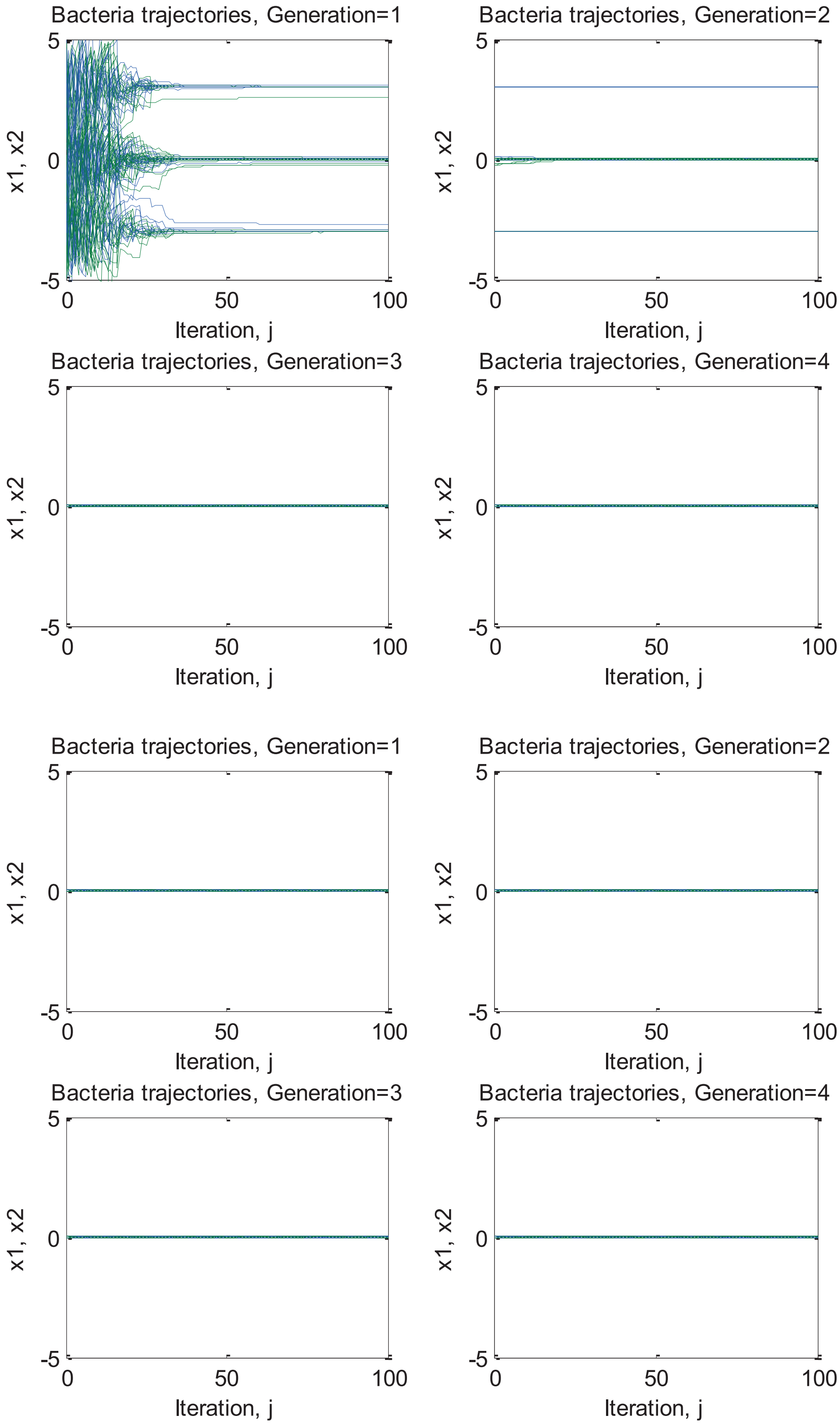

Figure 3.20 Bacterial motion trajectories for Example 3.4

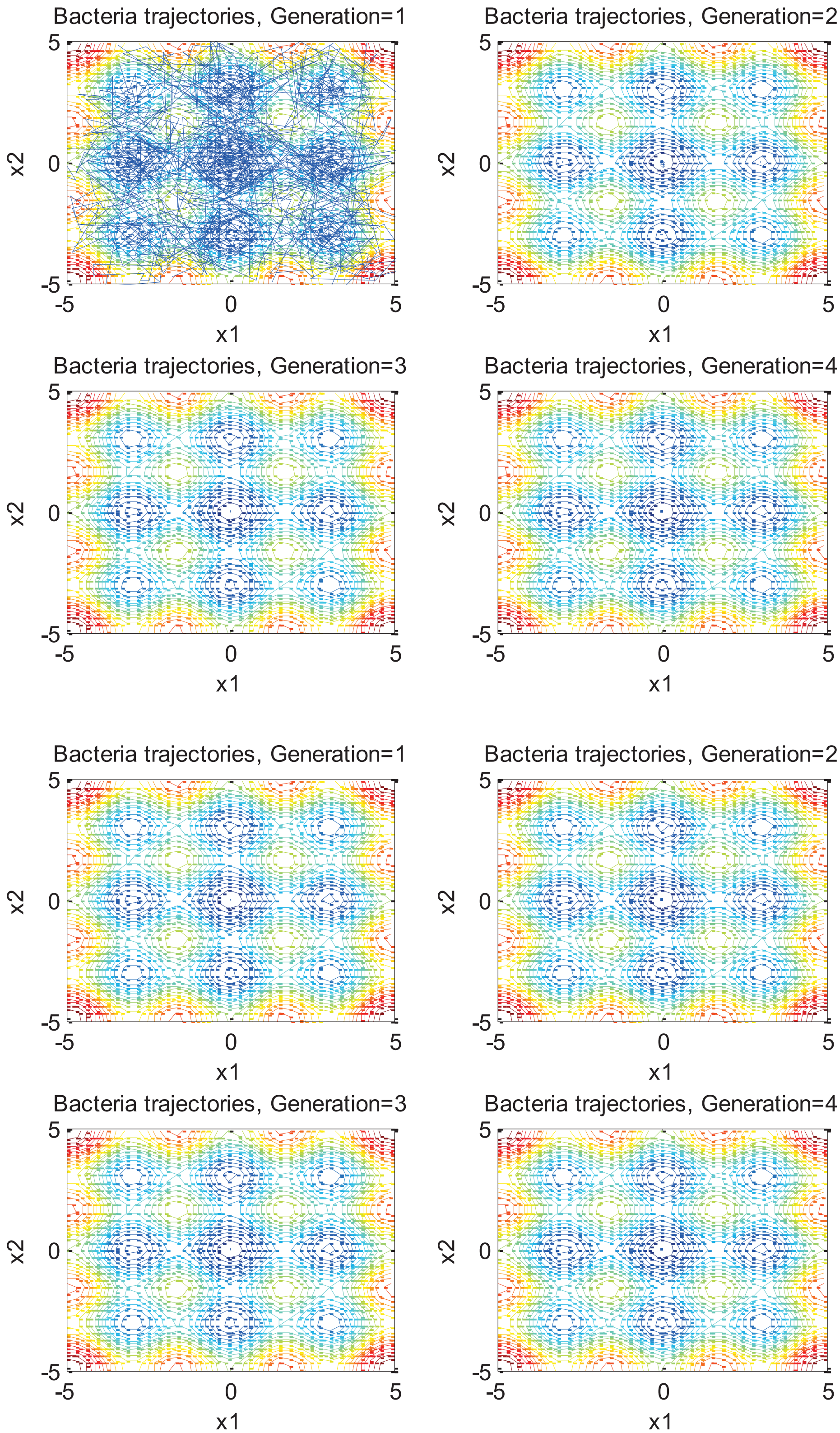

Figure 3.21　Motion trajectories on contour plots for Example 3.4

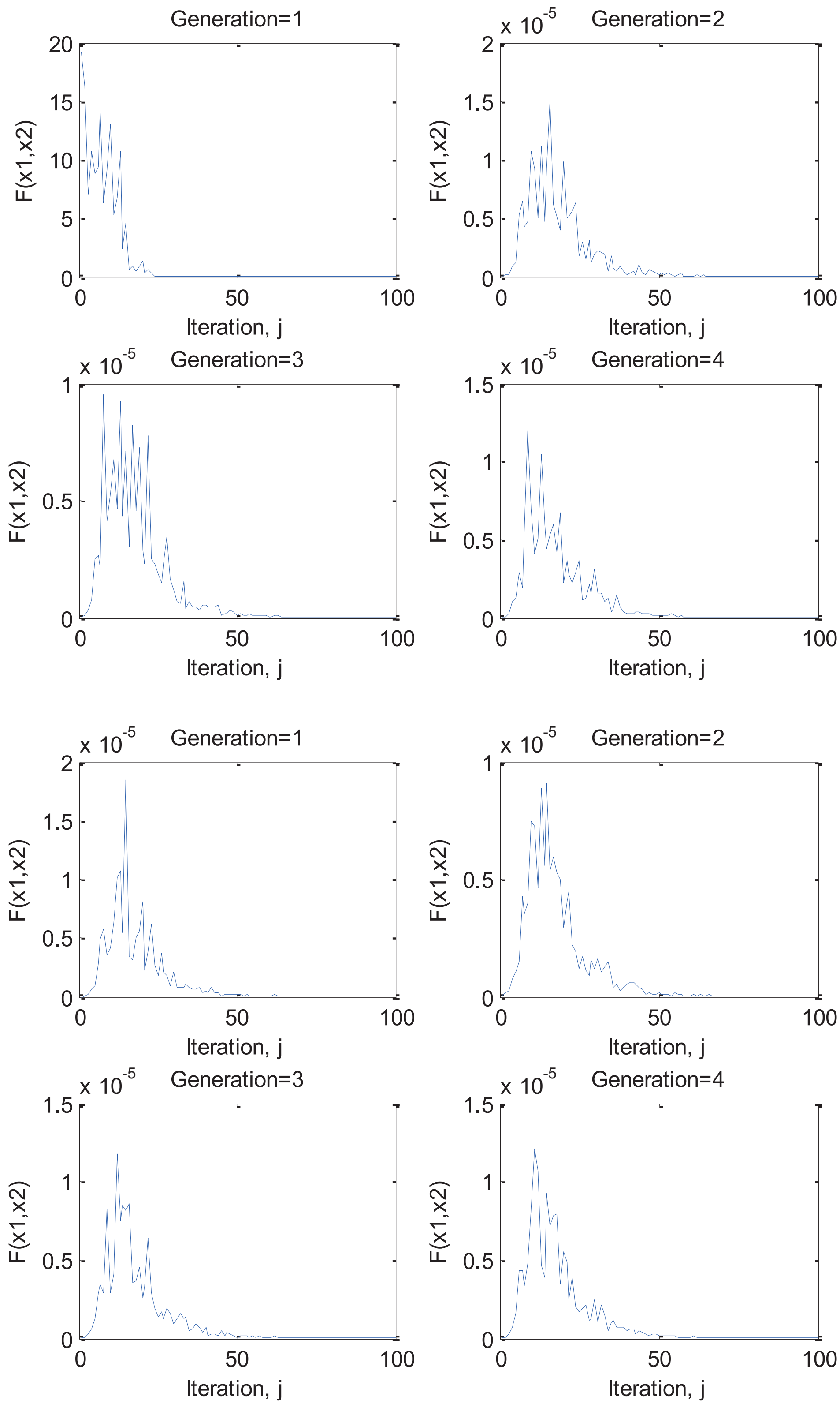

Figure 3.22 Objective function vs. iteration number for Example 3.4

Example 3.5:

In this example the Schaffer function is implemented and minimized using the MBFA. To find the global minimum for this function, the algorithm must have the ability to avoid getting trapped in the local minima. The challenge in this optimization problem comes from the shape of the function which has multi-minimum points as shown in Figure 3.23.

$$\textit{minimize} \qquad F(x_1,x_2)=0.5+\frac{\sin^2\left(\sqrt{x_1^2+x_2^2}\right)-0.5}{\left(1+0.001(x_1^2+x_2^2)\right)^2} \tag{3.40}$$

$$\text{subject to} \qquad -10\le x_1,x_2\le 10 \tag{3.41}$$

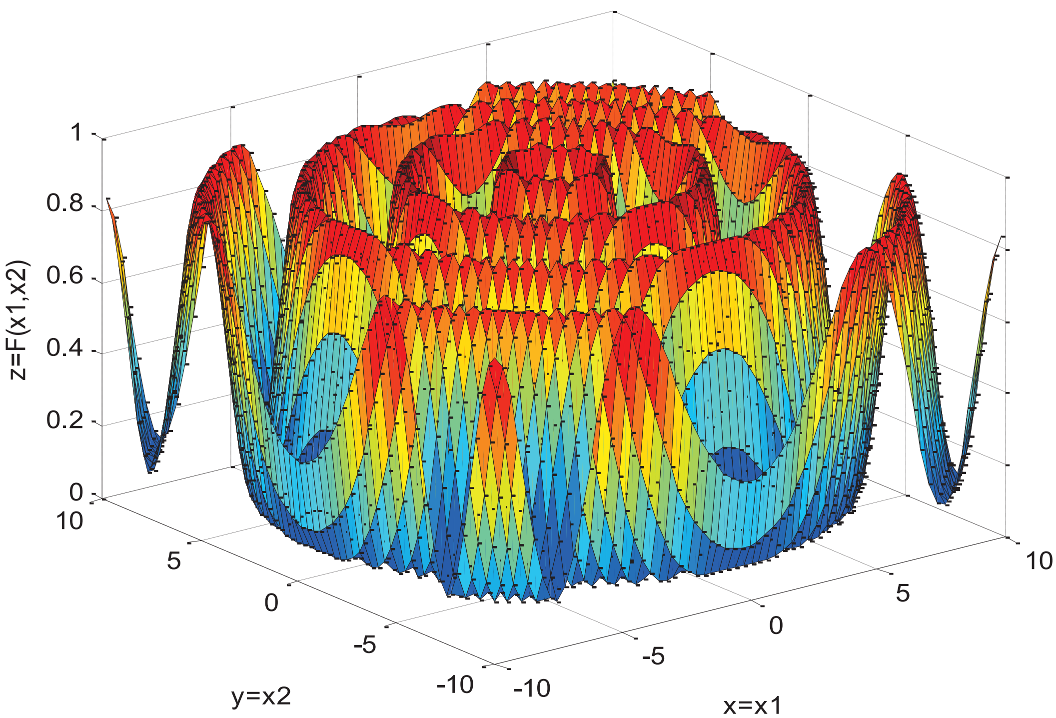

Figure 3.23 Optimization function of Example 3.5

The solution for the Schaffer function is the global minimum $f(x_1^*,x_2^*)=0$ at $(0,0)$ which obtained using the MBFA as shown in Table 3.5. The search operations are illustrated in Figure 3.24, Figure 3.25 and Figure 3.26.

Table 3.5 Results for Example 3.5

Solution		Objective			Average time (sec)
x_1	x_2	Min	Max	Average	
8.64e-008	-7.1313e-007	5.1648e-013	2.6125e-011	1.2541e-011	0.0974438

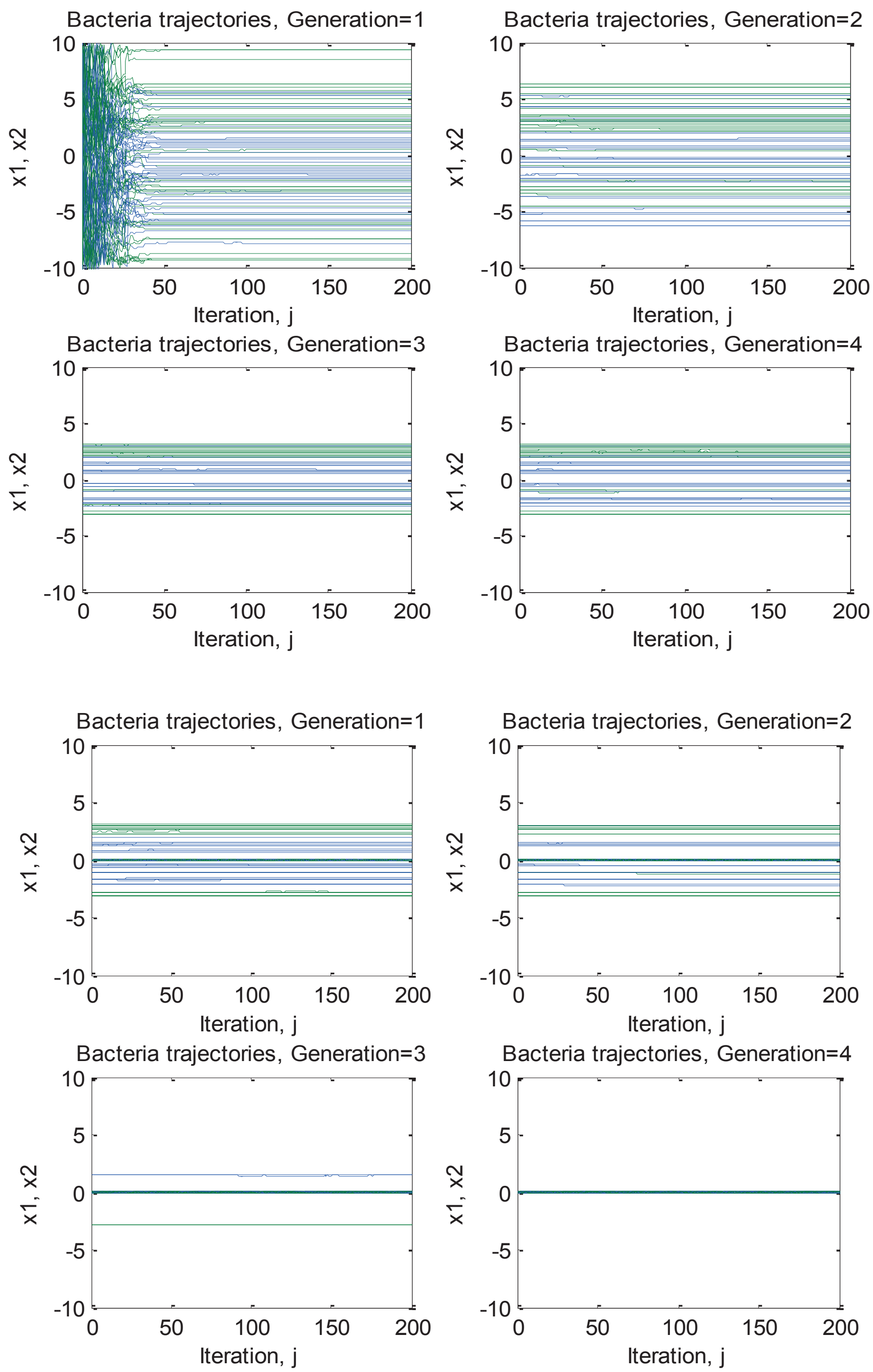

Figure 3.24   Bacterial motion trajectories for Example 3.5
(2 elimination/dispersal events)

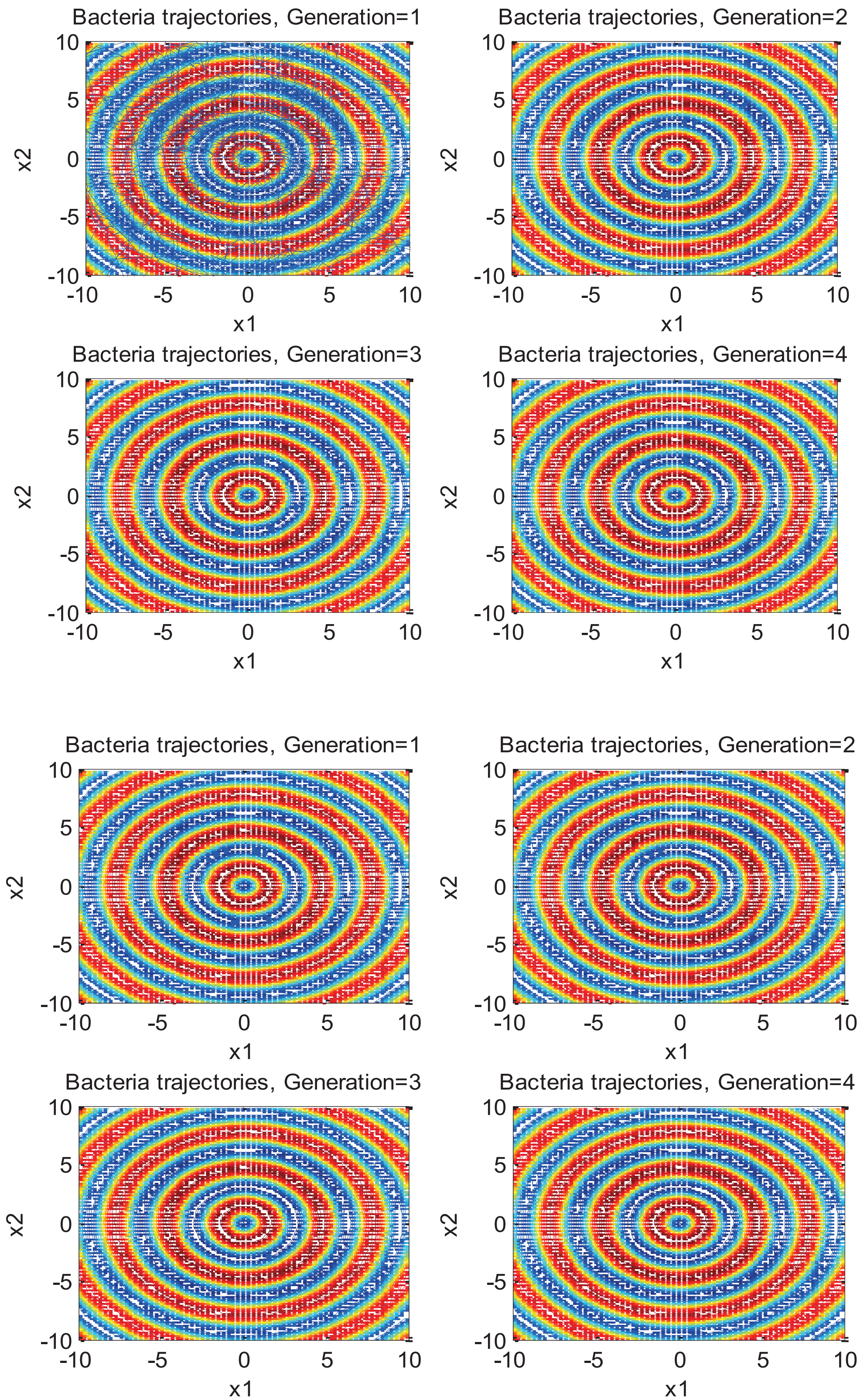

Figure 3.25 Motion trajectories on contour plots for Example 3.5
(2 elimination/dispersal events)

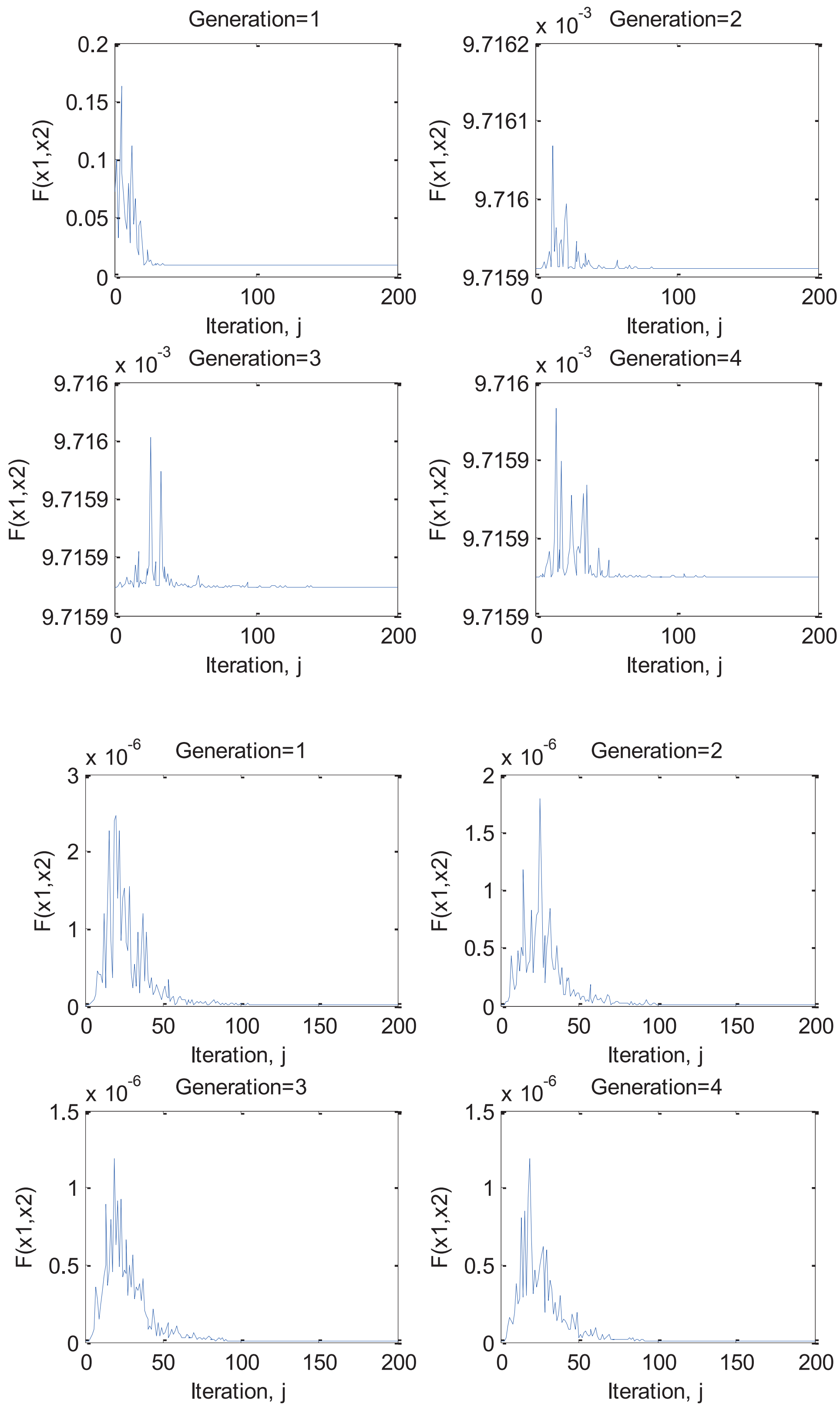

Figure 3.26 Objective function vs. iteration number for Example 3.5

Example 3.6:

To demonstrate the effectiveness of the constraint-handling mechanism of the proposed algorithm, it is applied to solve the following constrained optimization problem:

$$\textit{minimize} \quad F(x_1,x_2)=x_1^4-2x_2x_1^2+x_1^2+x_1x_2^2-2x_1+4 \tag{3.42}$$

$$\text{subject to:} \quad x_1^2+x_2^2-2=0 \tag{3.43}$$

$$0.25x_1^2+0.75x_2^2-1\le 0 \tag{3.44}$$

$$0\le x_1,x_2\le 5 \tag{3.45}$$

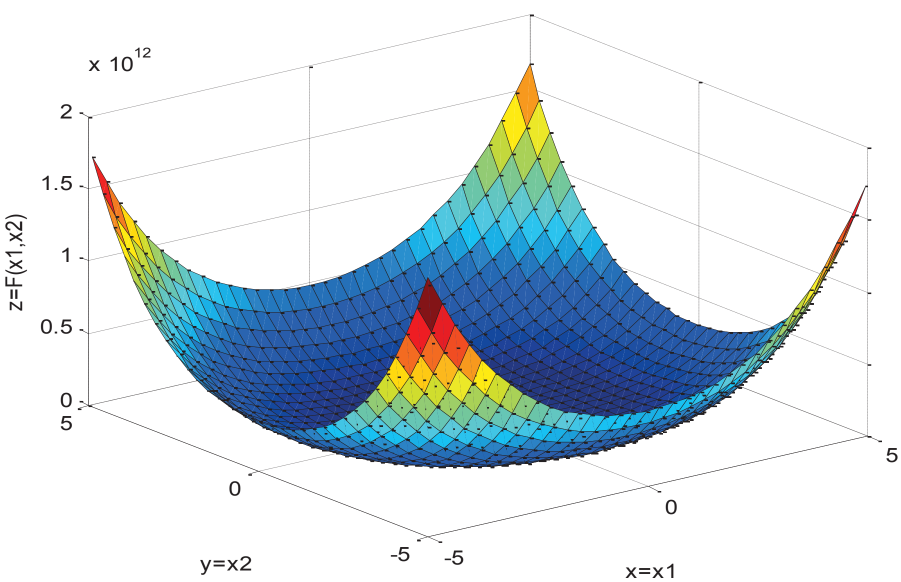

Figure 3.27 Constrained optimization function of Example 3.6

The function has both inequality and equality constraints. The function is depicted in Figure 3.27. The proposed algorithm could find the near optimal solution and hence, the effectiveness of the used constraint-handling approach is demonstrated. Results obtained by applying the proposed algorithm are tabulated in Table 3.6. Figure 3.28, Figure 3.29 and Figure 3.30 show the trajectories of the algorithm and the search paths.

Table 3.6 Results for Example 3.6

Solution		Objective			Average time (sec)
x_1	x_2	Min	Max	Average	
1.0000	1.0000	3.0000	3.0006	3.0001	0.0841742

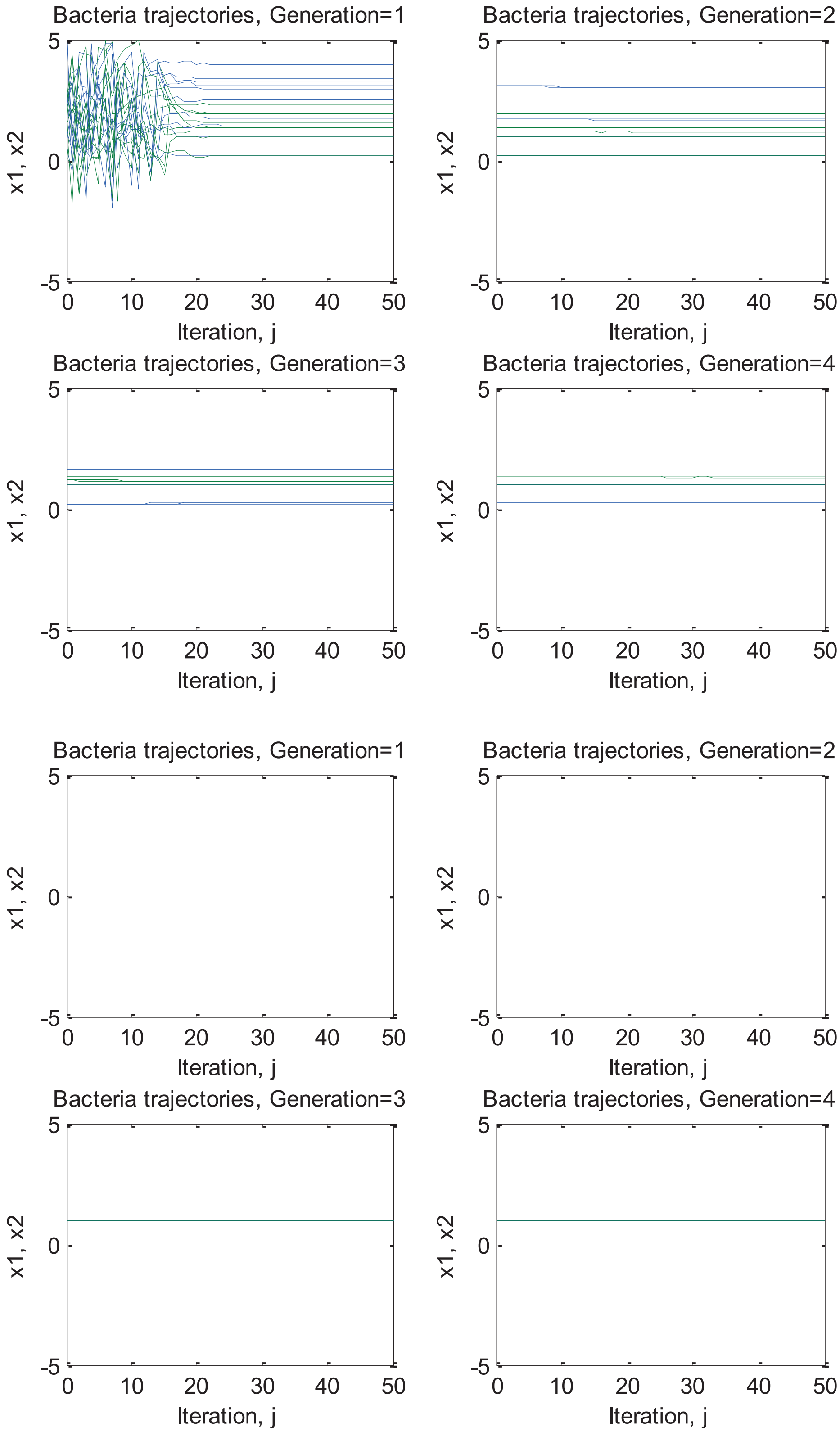

Figure 3.28 Bacterial motion trajectories for Example 3.6
(2 elimination/dispersal events)

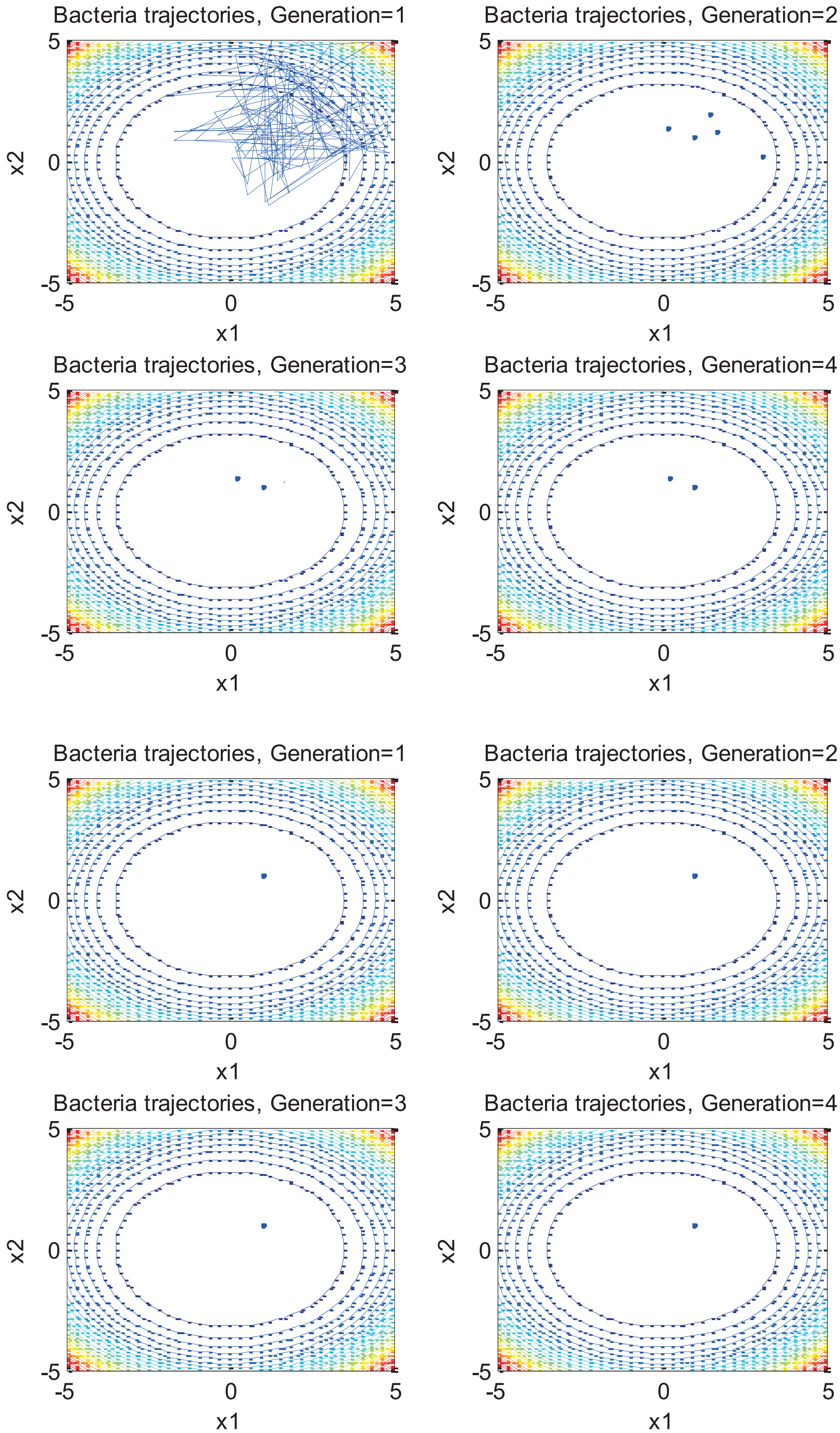

Figure 3.29 Motion trajectories on contour plots for Example 3.6
(2 elimination/dispersal events)

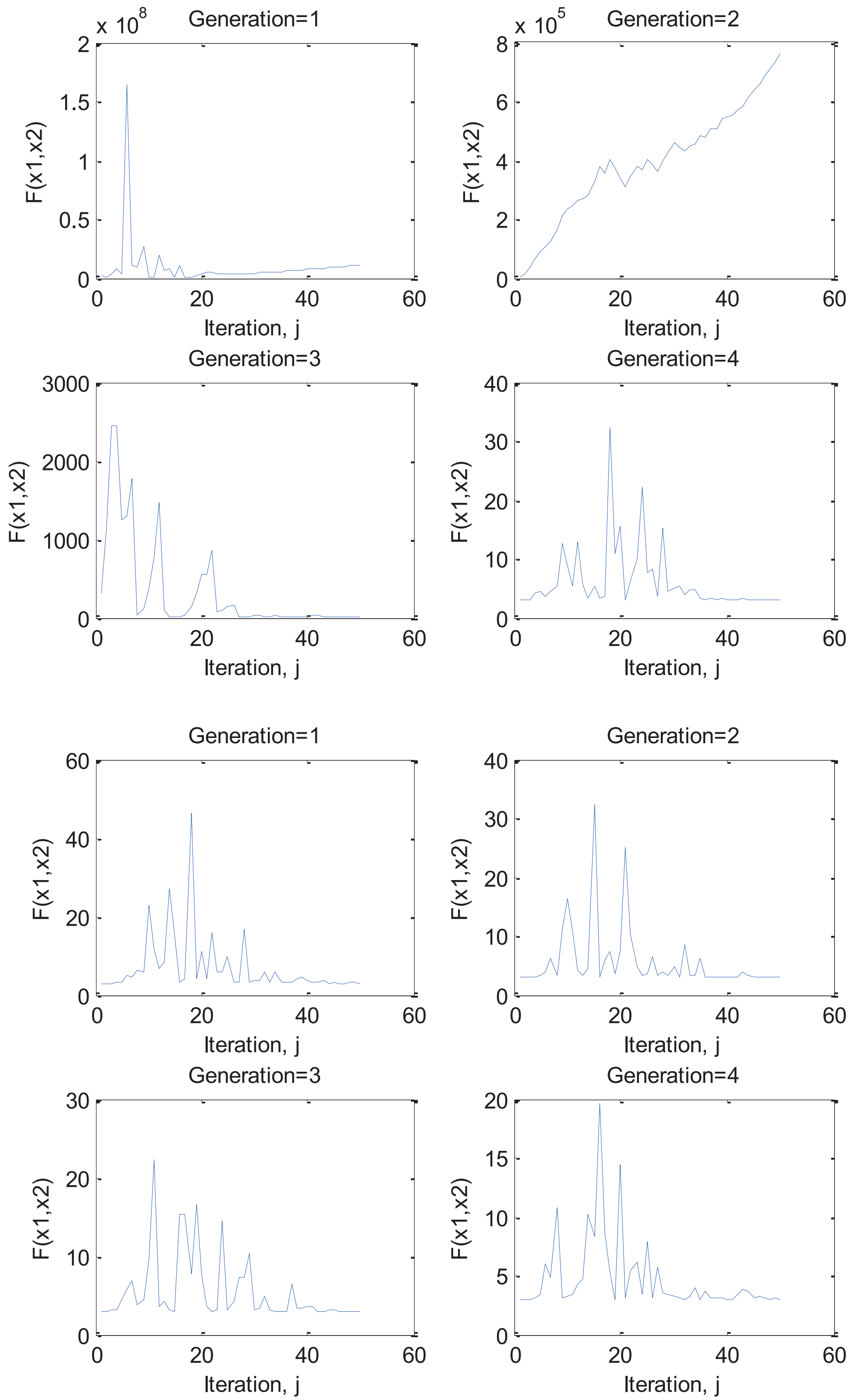

Figure 3.30 Objective function vs. iteration number for Example 3.6

Example 3.7:

This example is devoted to solve a sample multi-objective optimization problem of two objective functions presented as follows [248]:

$$\textit{minimize} \quad \begin{cases} F_1(\vec{x}) = 200\left(2x_1 + \sqrt{2}x_2 + \sqrt{x_3} + x_4\right) \\ F_2(\vec{x}) = 0.01\left(\dfrac{2}{x_1} + \dfrac{2\sqrt{2}}{x_2} - \dfrac{2\sqrt{2}}{x_3} + \dfrac{2}{x_4}\right) \end{cases} \tag{3.46}$$

$$\text{subject to:} \quad \begin{cases} 1 \le x_1 \le 3 \\ \sqrt{2} \le x_2 \le 3 \\ \sqrt{2} \le x_3 \le 3 \\ 1 \le x_4 \le 3 \end{cases} \tag{3.47}$$

The MBFA is applied to solve this multi-objective optimization problem using the weighted-sum method described in 3.3.3.1 above. The multi-objective optimization problem is converted into a single-objective one by assigning weighting factors to each objective function. The parameters of the algorithm are fixed as in the previous example. The non-dominated solutions are obtained and presented in Table 3.7. The table also shows the weights for each function and the solution computed corresponding to each solution. The Pareto optimal trade-off curve, which represents the set of the non-dominated solutions, is illustrated in Figure 3.31.

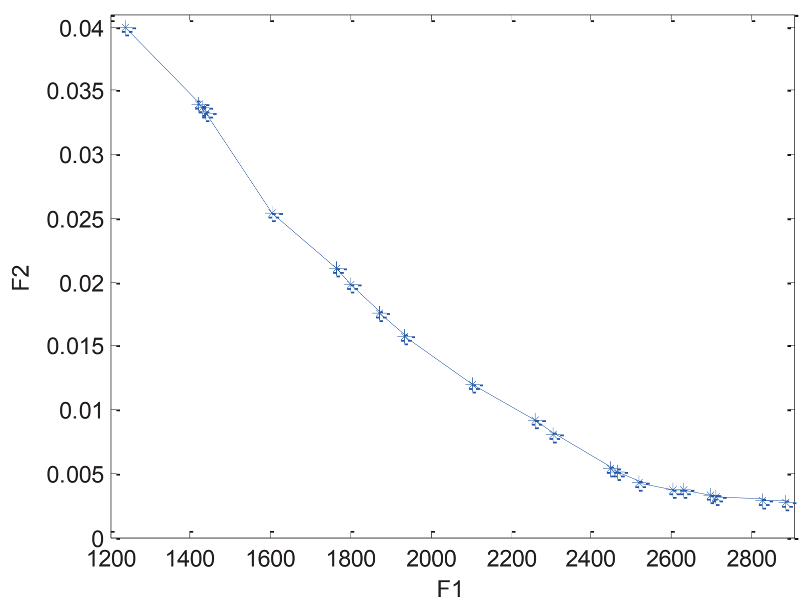

Figure 3.31 Pareto optimal front for Example 3.7

Table 3.7 Pareto optimal set of solutions for Example 3.7

Solution	Weight		Objective		Solution			
Number	w_1	w_2	F_1	F_2	x_1	x_2	x_3	x_4
1	1.00	0.00	1237.763	0.0400	1.000	1.414	1.414	1.000
2	0.95	0.05	1419.335	0.0340	1.054	1.735	1.641	1.254
3	0.90	0.10	1428.250	0.0333	1.060	1.739	1.628	1.286
4	0.85	0.15	1437.343	0.0333	1.086	1.730	1.667	1.277
5	0.80	0.20	1603.512	0.0246	1.295	2.007	1.455	1.383
6	0.75	0.25	1765.558	0.0221	1.047	2.422	1.539	2.068
7	0.70	0.30	1801.969	0.0198	1.401	2.170	1.560	1.890
8	0.65	0.35	1871.762	0.0196	1.491	2.282	1.663	1.860
9	0.60	0.40	1935.699	0.0157	1.661	1.946	1.470	2.392
10	0.55	0.45	2103.569	0.0129	1.713	2.785	1.472	1.940
11	0.50	0.50	2257.941	0.0091	1.991	2.615	1.415	2.420
12	0.45	0.55	2305.076	0.0087	1.961	2.797	1.430	2.452
13	0.40	0.60	2448.745	0.0071	2.434	2.736	1.410	2.319
14	0.35	0.65	2497.940	0.0066	2.486	2.785	1.414	2.390
15	0.30	0.70	2517.292	0.0063	2.490	2.657	1.423	2.656
16	0.25	0.75	2603.557	0.0058	2.758	2.710	1.414	2.480
17	0.20	0.80	2628.669	0.0050	2.548	2.908	1.421	2.743
18	0.15	0.85	2689.861	0.0034	2.666	2.918	1.355	2.825
19	0.10	0.90	2705.069	0.0034	2.755	2.977	1.352	2.642
20	0.05	0.95	2833.479	0.0029	2.976	2.989	1.389	2.811
21	0.00	1.00	2886.370	0.0028	3.000	3.000	1.414	3.000

3.8 Summary

In this chapter, a brief introduction to optimization theory has been presented. An overview of the main concepts of both single-objective and multiple-objective optimization has been provided. Various approaches used to solve single and multiple-objective optimization problems have also been demonstrated in the chapter. Classification of various optimization problems and solution methods has been highlighted. In addition, major differences between classical and non-classical methods have been emphasized. The main subject of the chapter is the BFA as it is the optimization methodology used in this work. The various aspects of the basic BFA are addressed from both biological and optimization-based perspectives. The modifications that are proposed in this thesis to improve the performance of the original algorithm and enhance its convergence characteristics have been introduced, discussed and validated. The constraint-handling mechanism, which is implemented in this thesis, has been demonstrated and discussed since the problems that are tackled in this thesis are multi dimension constrained problems. Selected numerical examples have been employed to validate the proposed MBFA and to demonstrate its capabilities as a powerful, robust and reliable optimization technique. All the problems and case studies in the next chapters are solved using the techniques presented in this chapter.

CHAPTER 4 ECONOMIC LOAD DISPATCH OF ALL-THERMAL POWER GENERATION

4.1 INTRODUCTION

Economic operation and planning of electrical power systems have always been a primary concern in the electrical power industry. Optimal economic operation of power generation systems is achieved through the efficient use of the available fuel which comes mostly from irreplaceable natural resources. An imperative truth that raises the importance of the optimal economic operations is that the electrical energy cannot be stored in large amounts. In addition, significant reduction in the amount of fuel used and hence in the operating costs can be achieved by a small percent of savings in power generation systems. Operating costs of different generating units are dissimilar due to various reasons such as their characteristics and efficiencies and the distances between their locations and load centers. Consequently, an optimal power generation schedule that determines the generation level of each of the units is essential to meet the load demand at the minimum cost. Furthermore, the operating cost of a specific generating unit is not linearly dependent on the power it produces. In fact, this relationship is a nonlinear and even non-smooth function as will be shown in the next section. Obtaining the optimal economic generation schedule can only be realized by considering various operational constraints and limitations. The load demand, for instance, must be satisfied all the time while including the system losses that are function of the power generation. Other practical issues such as the valve-point effects and reserve margins considered by the generation patterns need to be taken into consideration.

This chapter is devoted to the economic load dispatch of exclusively thermal electric power systems. The MBFA presented in Chapter 3 is applied to solve the ED problem. The problem will firstly be assumed as a lossless case where the transmission losses are neglected. Subsequently, the power losses are considered in addition to the valve-point effects. Several test systems are used to validate the performance of the proposed algorithm and to compare the results to those obtained using other well-known optimization techniques.

4.2 Thermal Generation Plant: Operating Cost Modeling

The total cost of operating thermal plants includes cost of labor and maintenance in addition to the costs of fuel and other supplies. In general, the economic dispatch process considers the cost of the fuel burnt in the fossil units. This does not mean that the other costs are neglected but they are commonly assumed to be a fixed percentage of the incoming fuel costs [3]. As a result of a mechanical process, energy is produced and transformed into mechanical form through steam or combustion turbines. The electric generator is driven by the turbine and hence, energy is finally transformed into electrical form. The power output of this system is connected to the electric power load. In addition, it supplies the auxiliary power system requirements of the plant itself. Figure 4.1 is a schematic illustration of a typical turbine-generator unit.

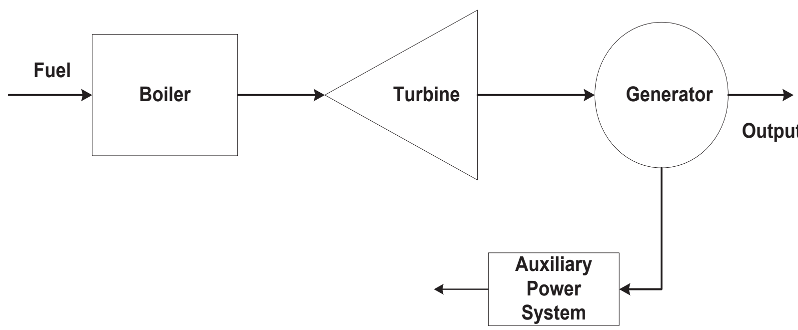

Figure 4.1 Typical turbine-generator model

The input to the thermal plant is generally measured in MBtu/h and the output power is in MW. Typical net heat rates for various fossil generating unit sizes are given in the appendix [3]. The input-output relation of a thermal unit, which is known as "heat-rate" curve, is shown in Figure 4.2 [249].

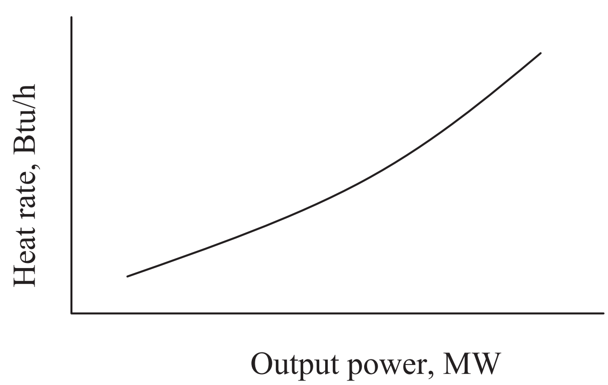

Figure 4.2 Heat-rate curve

The heat-rate curve is converted to the fuel cost curve representing the relationship of the operating cost of a fossil-fired thermal unit and its output power as shown in Figure 4.3. This cost is usually approximated as a quadratic function of the real power generation

$$F_i(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + c_i \tag{4.1}$$

Typical values of the coefficients a_i, b_i and c_i as well as typical heat rate data for various fossil generation units are provided in the appendix [3].

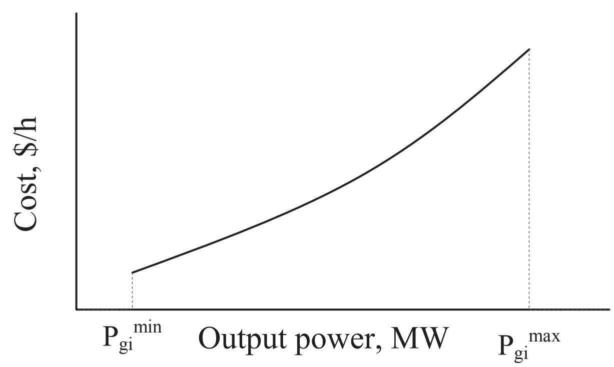

Figure 4.3 Fuel cost curve

The lower limit of the output power $P_{gi}^{\min}$ is the minimum economical loading limit below which the operation is infeasible technically and/or economically. On the other hand, $P_{gi}^{\max}$ represents the upper limit and the maximum output power.

The derivative of the fuel cost curve with respect to the active power results in an important characteristic which is a measure of the cost of the next increment of power. This relationship, which is shown in Figure 4.4, is known as the "incremental fuel-cost" curve.

$$\frac{dF_i(P_{gi})}{dP_{gi}} = 2a_i P_{gi} + b_i \tag{4.2}$$

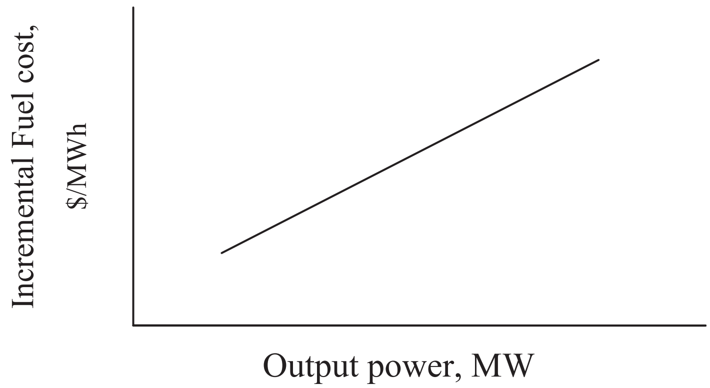

Figure 4.4 Incremental fuel-cost curve

4.3 ECONOMIC DISPATCH PROBLEM

The economic dispatch problem is designed to determine the optimal loading of all committed generating units to minimize the cost function subject to the system constraints [2]. These running generating units are assumed to be known in advance. It is also assumed that the information about the daily load demand is also available. Accordingly, assuming that the number of committed units is N_g and the total load demand is P_D, then the ED problem can be formulated with the following objective function:

$$\textit{Minimize} \quad F_T = \sum_{i=1}^{N_g} F_i(P_{gi}) \tag{4.3}$$

This is subject to operational equality and inequality constraints as follows:

- Load balance equation

$$\sum_{i=1}^{N_g} P_{gi} - P_D = 0 \tag{4.4}$$

- Generating unit capacity limits

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, i = 1, 2, \ldots, N_g \tag{4.5}$$

where

$F_i(P_{gi})$: operating cost for unit i

P_{gi} : active power generation for unit i

P_D : total load demand

N_g : number of thermal generating units

$P_{gi}^{\min}$: minimum power generation for unit i

$P_{gi}^{\max}$: maximum power generation for unit i

The formulation expressed above is for the basic model of the conventional ED problem. Later in this chapter more practical aspects will be considered such as the system losses and the valve-point effects. It should be noted that the results of the ED solution of an all-thermal system can be applied to a hydro-thermal system by considering an equivalent thermal characteristics [3].

The proposed MBFA is implemented to determine the optimal ED of the case studies shown in the following sections. Some of these cases represent the ED problem considering the system losses and others include the valve-point-effects in their objective functions as will be discussed later in this chapter. The algorithm was implemented in MATLAB 7.8 and executed on an Intel Core 2 Duo 1.66 GHz personal computer. In order to check for consistency, in each test case at least 30 independent runs were conducted with different random initial solution for each run. Results obtained for each case are compared with those of other methods. The comparison is performed against various approaches that include deterministic and heuristic methods. The various MBFA parameters are tuned separately as they are problem-dependent. As an attempt to come across the optimum parameter combinations, a very large number of preliminary runs were executed independently for each case study. The execution time for each run was recorded accurately (or at least as accurate as possible). This accuracy was maintained through rebooting the machine before each simulation. Furthermore, it should be mentioned that the runs were executed in such a way that no other applications were running simultaneously on the computer. Regarding the dynamic run-length functions discussed in Section 3.6.1, both the linear and nonlinear decreasing functions of Equations (3.28) and (3.29) were separately applied to the algorithm in each case study.

To select one of these two functions, the one which gave best results and/or lowest CPU computation time was considered.

4.4 OPTIMAL ECONOMIC DISPATCH: TRANSMISSION LOSSES NEGLECTED

The ED problem considered in this section deals with thermal generation systems where the transmission losses are neglected. In this configuration it is assumed that all the generating units are connected to the same bus as shown in Figure 4.5.

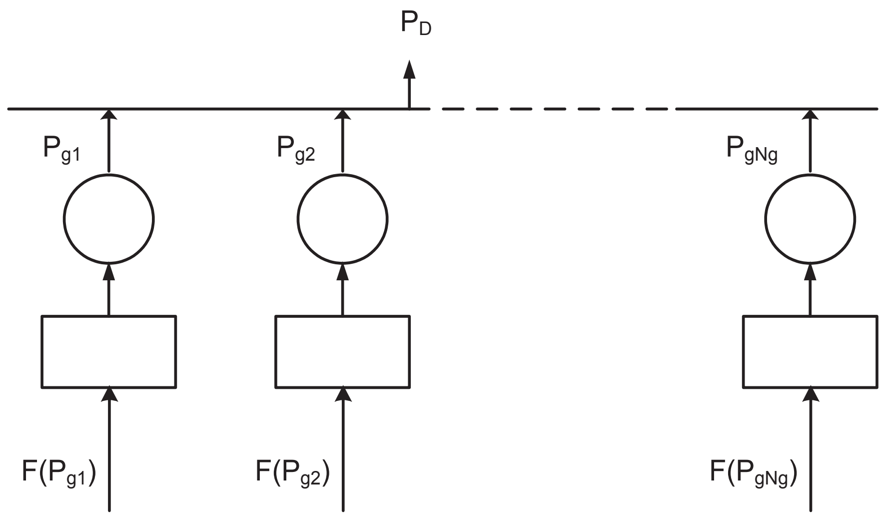

Figure 4.5 N_g generating units connected to a common bus to supply a load P_D

4.4.1 Case Study 1: 3-Generator System

This case study is a 3-generator system and a total load demand of 850 MW [2]. The objective in this case is to determine the optimal economic power schedule for the three generating units. The fuel cost functions for the units are given as follows:

$$F_1(P_{g1}) = 0.001562P_{g1}^2 + 7.92P_{g1} + 561 \quad \$/h \tag{4.6}$$

$$F_2(P_{g2}) = 0.00194P_{g2}^2 + 7.85P_{g2} + 310 \quad \$/h \tag{4.7}$$

$$F_3(P_{g3}) = 0.00482P_{g3}^2 + 7.97P_{g3} + 78 \quad \$/h \tag{4.8}$$

The high and low limits of the three units are represented by the following inequalities:

$$150MW \le P_{g1} \le 600MW \tag{4.9}$$

$$100MW \le P_{g2} \le 400MW \tag{4.10}$$

$$50MW \le P_{g3} \le 200MW \tag{4.11}$$

The transmission losses of this system are neglected. The MBFA is used to determine the optimal load dispatch and the results are shown in Table 4.1.

Table 4.1   Results of 30 runs (3-generator lossless system 1)

Power dispatch			Cost ($/h)			Average time (sec)
P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	Min	Max	Average	
392.98	334.42	122.60	8194.36	8196.00	8194.99	0.2523

Results obtained by the proposed MBFA are compared with those obtained using the Lambda Iteration Method (LIM) [2], Particle Swarm Optimization (PSO) [250] and the Pattern Search (PS) approach [251]. The comparison is presented in Table 4.2 which shows that the proposed method gives a very close solution or a slightly lower cost than those of other methods.

Table 4.2   Comparison of the results (3-generator losses system 1)

Power	Method			
dispatch	LIM [2]	PSO [250]	PS [251]	MBFA
P_{g1} (MW)	393.20	391.80	393.20	392.98
P_{g2} (MW)	334.60	338.20	334.60	334.42
P_{g3} (MW)	122.20	120.00	122.20	122.60
Cost ($/h)	8194.36	8194.40	8194.36	8194.36

4.4.2 Case Study 2: 3-Generator System

The same system of Case Study 1 is considered with the fuel cost function of the generating unit 1 changed due to the decrease of the coal price. The cost function of this unit becomes:

$$F_1(P_{g1}) = 0.00128P_{g1}^2 + 6.48P_{g1} + 459 \quad \$/h \tag{4.12}$$

The proposed MBFA is applied to this system to find the optimal ED. Table 4.3 and Table 4.4 show the solution and the comparison of the results with those obtained by the other optimization methods mentioned above.

Table 4.3   Results of 30 runs (3-generator lossless system 2)

Power dispatch			Cost ($/h)			Average time (sec)
P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	Min	Max	Average	
601.83	186.58	61.60	7251.82	7253.79	7252.11	0.2453

Table 4.4 Comparison of the results (3-generator losses system 2)

Power dispatch	Method			
	LIM [2]	PSO [250]	PS [251]	MBFA
P_{g1} (MW)	600.00	599.90	600.00	600.00
P_{g2} (MW)	187.10	187.40	187.10	186.58
P_{g3} (MW)	62.20	62.70	62.20	61.59
Cost ($/h)	7252.83	7252.85	7252.83	7251.82

It can be seen from the tables that the cost obtained using the MBFA is lower than those obtained by the other optimization techniques.

4.5 Optimal Economic Dispatch: Transmission Losses Considered

In power systems where electrical energy is transmitted using long transmission lines, network losses cannot be neglected as they significantly affect the generation dispatch. In practical systems, it is estimated that the system power losses can be as much as 5% to 10% of the total power generation [252, 253]. To include the transmission losses, an all-thermal generation system is configured as shown in Figure 4.6. The generating units in this system are connected to an equivalent load bus through a transmission network [2]. In the ED problem of this section, the transmission losses are included in the load balance Equation (4.4). Accordingly, the objective function expressed in Equation (4.3) is to be minimized while satisfying the following active power balance equation:

$$\sum_{i=1}^{N_g} P_{gi} - P_D - P_L = 0 \tag{4.13}$$

where P_L is the active power losses as a function of only the real power generation. The real power transmission losses in power systems are principally computed using the exact power flow equations. However, it is a common practice to express the losses as a quadratic function only in terms of real power generation. This function is referred to as the loss formula and its simplest form is known as George's formula [3]:

$$P_L = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_{g_i} B_{ij} P_{g_j} \tag{4.14}$$

The parameters B_{ij} are called the loss coefficients or *B*-coefficients. In order to obtain a more accurate loss formula, a linear term and a constant is added to the expression of (4.14) to form what is referred to as Kron's loss formula [3]:

$$P_L = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{g_i} B_{ij} P_{g_j} + \sum_{i=1}^{N_g} B_{i0} P_{g_i} + B_{00} \tag{4.15}$$

This formula can be expressed in a vector notation as the following:

$$\begin{aligned} P_L &= \begin{bmatrix} P_{g1} & P_{g2} & \dots & P_{gNg} \end{bmatrix} \begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1Ng} \\ B_{21} & B_{22} & \cdots & B_{2Ng} \\ \vdots & \vdots & \ddots & \vdots \\ B_{Ng1} & B_{Ng2} & \cdots & B_{NgNg} \end{bmatrix} \begin{bmatrix} P_{g1} \\ P_{g2} \\ \vdots \\ P_{gNg} \end{bmatrix} \\ &+ \begin{bmatrix} P_{g1} & P_{g2} & \dots & P_{gNg} \end{bmatrix} \begin{bmatrix} B_{01} \\ B_{02} \\ \vdots \\ B_{0Ng} \end{bmatrix} + B_{00} \end{aligned} \tag{4.16}$$

The *B*-coefficients mainly depend on the operating condition of the system. They are usually assumed to be constant parameters, unless the system operating state of a new generation scheduling is significantly different from the base case.

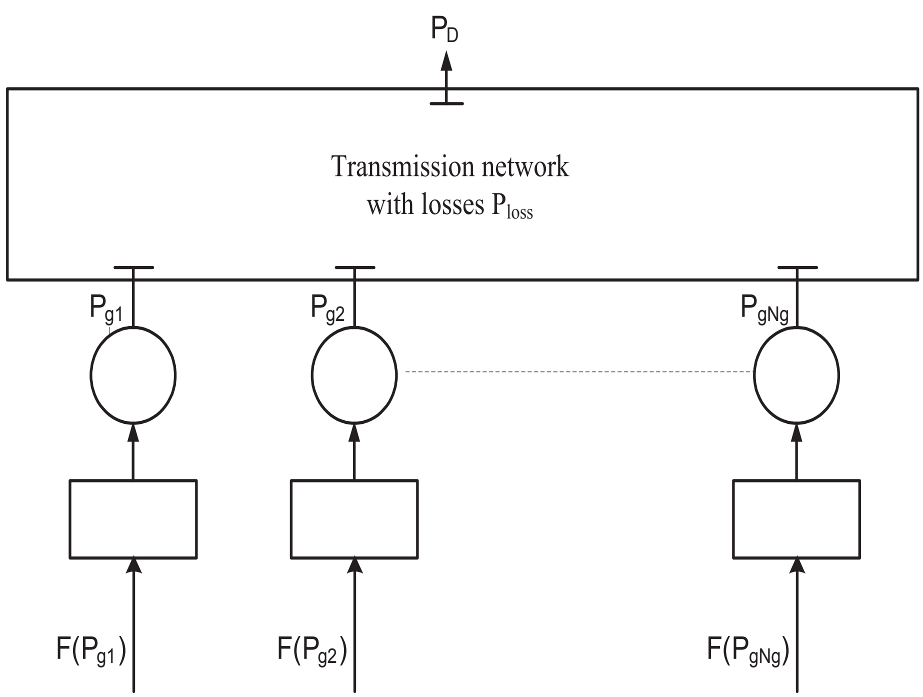

Figure 4.6 N_g generating units supplying load P_D through transmission network

4.5.1 Case Study 1: 3-Generator System

The same system with the same generating units and fuel costs of Section 4.4.1 above is considered in this case study with the following loss expression is included [2]:

$$P_L = 0.00003P_{g1}^2 + 0.00009P_{g2}^2 + 0.00012P_{g3}^2 \quad MW \tag{4.17}$$

The losses are included in the active power balance equation (4.13). The optimal power dispatch obtained using the proposed MBFA is shown in Table 4.5.

Table 4.5 Results of 30 runs (3-generator system with losses)

Power dispatch			P_{loss} (MW)	Cost ($/h)			Average time (sec)
P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)		Min	Max	Average	
435.60	299.60	130.60	15.82	8344.59	8346.21	8345.98	0.2426

Results show that the MBFA is able to determine a close to optimal solution with a good robustness and convergence characteristics. These results are compared with those obtained by the LIM [2], PSO [250] and the PS approach [251]. Table 4.6 shows that the proposed algorithm gives a very close power generation pattern and a little lesser cost than those of other methods.

Table 4.6 Comparison of the results (3-generator system with losses)

Power dispatch	Method			
	LIM [2]	PSO [250]	PS [251]	MBFA
P_{g1} (MW)	435.13	435.60	435.10	435.64
P_{g2} (MW)	299.99	298.90	300.00	299.58
P_{g3} (MW)	130.71	131.40	130.73	130.59
P_{loss} (MW)	15.83	15.80	15.8300	15.82
Cost ($/h)	8344.31	8344.36	8344.59	8344.19

4.5.2 Case Study 2: 6-Generator System

This case study is the IEEE30-bus system with 6 generators and a total load demand of 1800 MW and the fuel cost characteristics are given in Table 4.7 [157, 251]. It should be noted here that the upper and lower generation limits were not specified in the mentioned references.

Table 4.7 Data for the 6-generator system of Case Study 2

Unit i	Parameter				
	a_i	b_i	c_i	P_{gi}^{min}	P_{gi}^{max}
	$/MW^{2}h	$/MWh	$/h	MW	MW
1	0.002035	8.43205	85.6348	150	600
2	0.003866	6.41031	303.7780	150	600
3	0.002182	7.42890	847.1484	150	600
4	0.001345	8.30154	274.2241	150	600
5	0.002182	7.42890	847.1484	150	600
6	0.005963	6.91559	202.0258	150	600

The system losses are taken into account using the loss formula of Equation (4.16) with the following loss coefficients matrix [251]:

$$B = 10^{-5}\begin{bmatrix} 20.0 & 1.0 & 1.5 & 0.5 & 0 & -3.0 \\ 1.0 & 30.0 & -2.0 & 0.1 & 1.2 & 1.0 \\ 1.5 & -2.0 & 10.0 & -1.0 & 1.0 & 0.8 \\ 0.5 & 0.1 & -1.0 & 15.0 & 0.6 & 5.0 \\ 0 & 1.2 & 1.0 & 0.6 & 25.0 & 2.0 \\ -3.0 & 1.0 & 0.8 & 5.0 & 2.0 & 21.0 \end{bmatrix} \tag{4.18}$$

Results obtained by the proposed MBFA are compared with those of the Surrogate Worth Trade-off with Newton-Raphson (SWT-NR) approach used in [157], the Sequential Quadratic Programming (SQP) method and the PS approach proposed in [251]. The results and comparison are presented in Table 4.8. This table shows that the proposed method gives very close results to those of other methods.

Table 4.8 Optimal Power dispatch (6-generator system)

Power dispatch	Method			
	SWT-NR [157]	SQP [251]	PS [251]	MBFA
P_{g1} (MW)	251.69	251.69	252.24	252.31
P_{g2} (MW)	303.78	303.79	306.70	303.32
P_{g3} (MW)	503.48	503.48	505.38	503.09
P_{g4} (MW)	372.32	372.32	365.13	372.74
P_{g5} (MW)	301.47	301.47	302.32	301.33
P_{g6} (MW)	197.40	197.40	198.53	197.32
P_{loss} (MW)	130.15	130.15	130.31	130.12
Cost ($/h)	18721.39	18721.39	18721.50	18721.39

Some statistical figures that illustrate the robustness of 30 runs of the algorithm are shown in Table 4.9. The standard deviation from the mean is 1.0987 with a range of 6.0281 between the minimum and maximum costs.

Table 4.9 Results of 30 runs (6-generator system)

Cost ($/h)					Average time (s)
Min	Max	Average	STD	Range	
18721.40	18727.42	18721.83	1.10	6.00	0.5629

4.5.3 Case Study 3: 20-Generator System

This system consists of 20 generators with a total demand of 2500 MW. The system data are shown in Table 4.10 and the B-coefficient matrix is as follows [254]:

Table 4.10 Data for the 20-generator system of Case Study 3

Unit i	Parameter				
	a_i	b_i	c_i	P_{gi}^{min}	P_{gi}^{max}
	$/MW²h	$/MWh	$/h	MW	MW
1	0.00068	18.19	1000	150	600
2	0.00071	19.26	970	50	200
3	0.00650	19.80	600	50	200
4	0.00500	19.10	700	50	200
5	0.00738	18.10	420	50	160
6	0.00612	19.26	360	50	100
7	0.00790	17.14	490	50	125
8	0.00813	18.92	660	50	150
9	0.00522	18.27	765	50	200
10	0.00873	18.92	770	30	150
11	0.00480	16.69	800	100	300
12	0.00310	19.76	970	150	500
13	0.00850	17.36	900	40	160
14	0.00511	18.70	700	20	130
15	0.00398	18.70	450	25	185
16	0.07120	14.26	370	20	80
17	0.00890	19.14	480	30	85
18	0.00713	18.92	680	30	120
19	0.00622	18.47	700	40	120
20	0.00773	19.79	850	30	100

$$B = 10^{-3}\begin{bmatrix}
8.70 & 0.43 & -4.61 & 0.36 & 0.32 & -0.66 & 0.96 & -1.60 & 0.80 & -0.10 & 3.60 & 0.64 & 0.79 & 2.10 & 1.70 & 0.80 & -3.20 & 0.70 & 0.48 & -0.70 \\
0.43 & 8.30 & -0.97 & 0.22 & 0.75 & -0.28 & 5.04 & 1.70 & 0.54 & 7.20 & -0.28 & 0.98 & -0.46 & 1.30 & 0.80 & -0.20 & 0.52 & -1.70 & 0.80 & 0.20 \\
-4.61 & -0.97 & 9.00 & -2.00 & 0.63 & 3.00 & 1.70 & -4.30 & 3.10 & -2.00 & 0.70 & -0.77 & 0.93 & 4.60 & -0.30 & 4.20 & 0.38 & 0.70 & -2.00 & 3.60 \\
0.36 & 0.22 & -2.00 & 5.30 & 0.47 & 2.62 & -1.96 & 2.10 & 0.67 & 1.80 & -0.45 & 0.92 & 2.40 & 7.60 & -0.20 & 0.70 & -1.00 & 0.86 & 1.60 & 0.87 \\
0.32 & 0.75 & 0.63 & 0.47 & 8.60 & -0.80 & 0.37 & 0.72 & -0.90 & 0.69 & 1.80 & 4.30 & -2.80 & -0.70 & 2.30 & 3.60 & 0.80 & 0.20 & -3.00 & 0.50 \\
-0.66 & -0.28 & 3.00 & 2.62 & -0.80 & 11.8 & -4.90 & 0.30 & 3.00 & -3.00 & 0.40 & 0.78 & 6.40 & 2.60 & -0.20 & 2.10 & -0.40 & 2.30 & 1.60 & -2.10 \\
0.96 & 5.04 & 1.70 & -1.96 & 0.37 & -4.90 & 8.24 & -0.90 & 5.90 & -0.60 & 8.50 & -0.83 & 7.20 & 4.80 & -0.90 & -0.10 & 1.30 & 0.76 & 1.90 & 1.30 \\
-1.60 & 1.70 & -4.30 & 2.10 & 0.72 & 0.30 & -0.90 & 1.20 & -0.96 & 0.56 & 1.60 & 0.80 & -0.40 & 0.23 & 0.75 & -0.56 & 0.80 & -0.30 & 5.30 & 0.80 \\
0.80 & 0.54 & 3.10 & 0.67 & -0.90 & 3.00 & 5.90 & -0.96 & 0.93 & -0.30 & 6.50 & 2.30 & 2.60 & 0.58 & -0.10 & 0.23 & -0.30 & 1.50 & 0.74 & 0.70 \\
-0.10 & 7.20 & -2.00 & 1.80 & 0.69 & -3.00 & -0.60 & 0.56 & -0.30 & 0.99 & -6.60 & 3.90 & 2.30 & -0.30 & 2.80 & -0.80 & 0.38 & 1.90 & 0.47 & -0.26 \\
3.60 & -0.28 & 0.70 & -0.45 & 1.80 & 0.40 & 8.50 & 1.60 & 6.50 & -6.60 & 10.7 & 5.30 & -0.60 & 0.70 & 1.90 & -2.60 & 0.93 & -0.60 & 3.80 & -1.50 \\
0.64 & 0.98 & -0.77 & 0.92 & 4.30 & 0.78 & -0.83 & 0.80 & 2.30 & 3.90 & 5.30 & 8.00 & 0.90 & 2.10 & -0.70 & 5.70 & 5.40 & 1.50 & 0.70 & 0.10 \\
0.79 & -0.46 & 0.93 & 2.40 & -2.80 & 6.40 & 7.20 & -0.40 & 2.60 & 2.30 & -0.60 & 0.90 & 11.0 & 0.87 & -1.00 & 3.60 & 0.46 & -0.90 & 0.60 & 1.50 \\
2.10 & 1.30 & 4.60 & 7.60 & -0.70 & 2.60 & 4.80 & 0.23 & 0.58 & -0.30 & 0.70 & 2.10 & 0.87 & 3.80 & 0.50 & -0.70 & 1.90 & 2.30 & -0.97 & 0.90 \\
1.70 & 0.80 & -0.30 & -0.20 & 2.30 & -0.20 & -0.90 & 0.75 & -0.10 & 2.80 & 1.90 & -0.70 & -1.00 & 0.50 & 11.0 & 1.90 & -0.80 & 2.60 & 2.30 & -0.10 \\
0.80 & -0.20 & 4.20 & 0.70 & 3.60 & 2.10 & -0.10 & -0.56 & 0.23 & -0.80 & -2.60 & 5.70 & 3.60 & -0.70 & 1.90 & 10.8 & 2.50 & -1.80 & 0.90 & -2.60 \\
-3.20 & 0.52 & 0.38 & -1.00 & 0.80 & -0.40 & 1.30 & 0.80 & -0.30 & 0.38 & 0.93 & 5.40 & 0.46 & 1.90 & -0.80 & 2.50 & 8.70 & 4.20 & -0.30 & 0.68 \\
0.70 & -1.70 & 0.70 & 0.68 & 0.20 & 2.30 & 0.76 & -0.30 & 1.50 & 1.90 & -0.60 & 1.50 & -0.90 & 2.30 & 2.60 & -1.80 & 4.20 & 2.20 & 0.16 & -0.30 \\
0.48 & 0.80 & -2.00 & 1.60 & -3.00 & 1.60 & 1.90 & 5.30 & 0.74 & 0.47 & 3.80 & 0.70 & 0.60 & -0.97 & 2.30 & 0.90 & -0.30 & 0.16 & 7.60 & 0.69 \\
-0.70 & 0.20 & 3.60 & 0.87 & 0.50 & -2.10 & 1.30 & 0.80 & 0.70 & -0.26 & -1.50 & 0.10 & 1.50 & 0.90 & -0.10 & -2.60 & 0.68 & -0.30 & 0.69 & 7.00
\end{bmatrix}$$

The proposed algorithm is applied and the results are compared to those obtained by the Hopfield model [254], the LIM and the PS approach [251]. Table 4.11 and Table 4.12 illustrate the results of the proposed algorithm. Compared to the other methods, the cost function achieved by the MBFA is significantly better than those obtained by LIM and the Hopfield model and slightly lower than that of the PS approach.

Table 4.11 Optimal Power dispatch (20-generator system)

Method	LIM [251]	Hopfield [254]	PS [251]	MBFA
Pg1 (MW)	512.7805	512.7804	501.7882	501.1087
Pg2 (MW)	169.1033	169.1035	169.1035	169.8707
Pg3 (MW)	126.8898	126.8897	126.8889	126.7146
Pg4 (MW)	102.8657	102.8656	102.8684	102.5186
Pg5 (MW)	113.6836	113.6836	113.6836	113.1788
Pg6 (MW)	73.5710	73.5709	72.1564	72.3594
Pg7 (MW)	115.2878	115.2876	116.7870	116.2285
Pg8 (MW)	116.3994	116.3994	116.3992	116.7992
Pg9 (MW)	100.4062	100.4063	100.4063	100.4807
Pg10 (MW)	106.0267	106.0267	106.0242	106.4783
Pg11 (MW)	150.2394	150.2395	150.2360	150.6603
Pg12 (MW)	292.7648	292.7647	304.0784	304.0278
Pg13 (MW)	119.1154	119.1155	119.1147	119.8005
Pg14 (MW)	30.8340	30.8342	30.8356	30.8067
Pg15 (MW)	115.8057	115.8056	115.8056	114.8279
Pg16 (MW)	36.2545	36.2545	36.4883	36.4071
Pg17 (MW)	66.8590	66.8590	66.8589	65.9225
Pg18 (MW)	87.9720	87.9720	87.9704	88.9900
Pg19 (MW)	100.8033	100.8033	100.8033	100.4793
Pg20 (MW)	54.3050	54.3050	54.3043	54.9011
P_{loss} (MW)	91.9671	91.9670	92.6012	92.5608
Cost ($/h)	62456.6391	62456.6341	62136.6612	62136.6502
Mean Time	33.7570	6.3550	----------------	0.8233

Table 4.12 Results of 30 runs (20-generator system)

Cost ($/h)					Average time (s)
Min	Max	Average	STD	Range	
62136.65	62230.08	62140.00	17.02	93.43	0.8233

4.6 Optimal Economic Dispatch: Valve-Point Effects Considered

In the previous sections, the ED problem is approximated by a smooth differentiable quadratic or piecewise quadratic objective function, which is the same approach used by classical optimization methods. However, due to the valve-point effects, the real input-output characteristics contain higher order nonlinearity and discontinuity which results in a non-convex, non-smooth fuel cost function. These discontinuities in the fuel cost curves are caused by sharp increases in throttle losses as a result of the effects of wire drawing at valve points. As a consequence of steadily lifting the valve, the losses decrease until the valve is fully open [3]. The valve-point effects on the generator fuel cost curve are illustrated in Figure 4.7. It is obvious that the incremental fuel cost curve shown in Figure 4.4 is also affected by the valve-point effects.

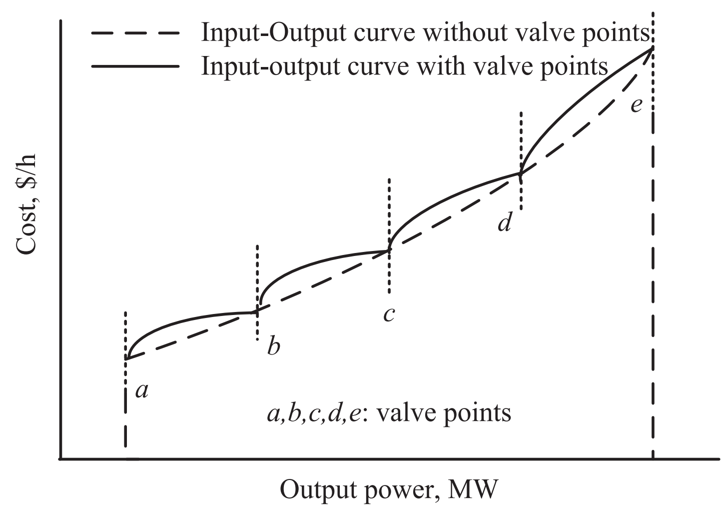

Figure 4.7 Fuel cost curve including valve-point effects

The valve-point effects are represented using two different approaches [255]. In the first, the effects are formulated as inequality constraints that represent them as prohibited operating zones [256, 257]. The second approach, which is considered in this section, includes a rectified sinusoidal term in the original objective function to model these effects [258-261]. Accordingly, the input-output characteristic function of Equation (4.1) is modified to obtain an accurate cost function model. The valve-point effects are included in the fuel cost function as follows [260, 262]:

$$F_i(P_{g_i}) = a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| e_i \sin\left(f_i (P_{g_i}^{\min} - P_{g_i}) \right) \right| \quad (4.19)$$

The coefficients e_i and f_i are constant fuel cost coefficients for unit i with valve-point effects. The total cost function to be minimized can be expressed as follows:

$$F_T = \sum_{i=1}^{N_g} a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| e_i \sin\left(f_i (P_{g_i}^{\min} - P_{g_i}) \right) \right| \quad (4.20)$$

In the following sections, the MBFA is applied to solve the ED problem considering the valve-point effects and power losses. The good performance of the proposed algorithm is demonstrated using several test systems in spite of the high dimensionality of the search hyperspace and the non-smoothness of the objective function due to the valve-point effects. Although traditional calculus-based optimization methods may show good performance in solving the conventional ED problem, they fail to achieve satisfactory results when used to solve ED problems with valve-point effects [263].

4.6.1 Case Study 1: 3-Generator System-Lossless Case

In this problem the system in Section 4.4.1 with 3 generators and a total load demand of 850 MW is studied. The test is performed without considering the network losses but the valve-point effects are included in the cost function. The coefficients of the system input-output characteristics and the valve-point effects are tabulated in Table 4.13 [259]:

Table 4.13 Data for Case Study 1 considering valve-point effects

	Generating Units		
Parameter	Unit 1	Unit 2	Unit 3
a_i	0.001562	0.00194	0.00482
b_i	7.92	7.85	7.97
c_i	561	310	78
e_i	300	200	150
f_i	0.0315	0.042	0.063
$P_{gi}^{min}(MW)$	100	100	50
$P_{gi}^{max}(MW)$	600	400	200

The proposed algorithm is applied and validated by comparing the results with those of the SQP, the PS [251] and the GA approach of [259]. The results obtained by proposed algorithm along with those of the three methods are shown in Table 4.14.

Table 4.14 ED for Case Study 1 (3-generator system with valve-point effects)

Power dispatch	Method			
	SQP [251]	GA [259]	PS [251]	MBFA
Pg_1 (MW)	399.200	300.000	300.300	300.161
Pg_2 (MW)	400.000	400.000	400.000	400.000
Pg_3 (MW)	50.800	150.000	149.700	149.801
Cost ($/h)	8241.60	8237.60	8234.10	8225.36

Compared to the GA and PS approaches, the cost function achieved by the MBFA is relatively lower while it is noticeably lower than that of the SQP deterministic method. The best cost obtained is 8225.36 $/h with a standard deviation of 4.53 from the mean and 15.96 range between the maximum and minimum costs obtained in 30 runs of the algorithm as shown in Table 4.15.

Table 4.15 Results of 30 runs (3-generator system with valve-point effects)

Cost ($/h)					Average time (sec)
Min	Max	Average	STD	Range	
8225.36	8241.33	8231.03	4.53	15.96	0.2121

4.6.2 Case Study 2: 3-Generator System-Losses Included

The same system of Case Study 1 above is considered here with taking into account the system losses. The *B*-coefficients are given in vector notation as follows [251]:

$$\mathbf{B} = \begin{bmatrix} 0.06760 & 0.00953 & -0.00507 \\ 0.00953 & 0.05210 & 0.00901 \\ -0.00507 & 0.00901 & 0.029400 \end{bmatrix} \tag{4.21}$$

$$\mathbf{B_0} = \begin{bmatrix} -0.07660 & -0.00342 & -0.01890 \end{bmatrix} \tag{4.22}$$

$$B_{00} = 0.040357 \tag{4.23}$$

The MBFA is successfully applied to solve this ED problem with its results compared to those of the methods listed in the last case study. These results and the comparison with the solution obtained by the three methods are shown in Table 4.16. Results are comparable with a little lower cost function obtained by the proposed MBFA.

Table 4.16 ED for Case Study 2 (3-generators with valve-point effects and losses)

Power dispatch	Method		
	SQP [251]	PS [251]	MBFA
Pg_1 (MW)	589.170	598.660	597.051
Pg_2 (MW)	399.200	394.500	395.281
Pg_3 (MW)	199.600	199.600	199.597
P_{loss} (MW)	337.966	342.760	341.929
Cost ($/h)	11471.54	11471.06	11458.01

The minimum, mean and maximum objective costs are shown in Table 4.17. The standard deviation and range between minimum and maximum costs are 6.48 and 25.05 respectively.

Table 4.17 Results of 30 runs (3-generators with valve-point effects and losses)

Cost ($/h)					Average time (sec)
Min	Max	Average	STD	Range	
11458.01	11483.05	11468.86	6.48	25.05	0.2754

4.6.3 Case Study 3: 13-Generator System

This test system consists of 13 generation units with 1800 MW load demand and the valve-point effects considered. The system data are shown in Table 4.18 and also presented in [264] and [261].

Table 4.18 Data for the 13-generator system of Case Study 3

	Parameter						
Unit *i*	a_i	b_i	c_i	ei	f_i	P_{gi}^{min} MW	P_{gi}^{max} MW
1	0.00028	8.10	550	300	0.035	0	680
2	0.00056	8.10	309	200	0.042	0	360
3	0.00056	8.10	307	150	0.420	0	360
4	0.00324	7.74	240	150	0.063	60	180
5	0.00324	7.74	240	150	0.063	60	180
6	0.00324	7.74	240	150	0.063	60	180
7	0.00324	7.74	240	150	0.063	60	180
8	0.00324	7.74	240	150	0.063	60	180
9	0.00324	7.74	240	150	0.063	60	180
10	0.00284	8.60	126	100	0.084	40	120
11	0.00284	8.60	126	100	0.084	40	120
12	0.00284	8.60	126	100	0.084	55	120
13	0.00284	8.60	126	100	0.084	55	120

According to the results obtained by the proposed MBFA, the optimal power generation of the units is as shown in Table 4.19. Convergence statistics are shown in Table 4.20.

Table 4.19 Optimal generation for the 13-generator system of Case Study 3

Unit	P_{gi}^{min} MW	P_{gi}^{max} MW	Optimal Generation MW
P_{g1}	0	680	525.6301
P_{g2}	0	360	252.9432
P_{g3}	0	360	257.6818
P_{g4}	60	180	78.3424
P_{g5}	60	180	83.4016
P_{g6}	60	180	89.9476
P_{g7}	60	180	87.3523
P_{g8}	60	180	100.9071
P_{g9}	60	180	131.1229
P_{g10}	40	120	40.4181
P_{g11}	40	120	40.7795
P_{g12}	55	120	55.8075
P_{g13}	55	120	55.6661

Table 4.20 Results of 30 runs (13-generator system with valve-point effects)

Cost ($/h)					Average time (sec)
Min	Max	Average	STD	Range	
17845.82	17901.02	17865.43	14.00	55.20	0.6361

Results of the proposed algorithm are compared to other methods' results. These are, EP [264], PSO, Hybrid EP with SQP (HEP-SQP), Hybrid Particle Swarm with SQP (HPSO-SQP) [263] and Chaotic Differential Evolution with SQP (CED-SQP) [265]. Table 4.21 shows this comparison. The proposed MBFA significantly outperformed all of the compared methods as it achieved a minimum cost of 17845.817 $/h which is a yearly saving of 815,818.80 $ compared to the lowest cost obtained by the other methods in the table.

Table 4.21 Comparison of the results (13-generator system with valve-point effects)

Method	Total Cost ($/h)	Average Time (s)
EP [264]	17994.07	157.4300
PSO [263]	18030.72	77.3700
HEP-SQP [263]	17991.03	121.9300
HPSO-SQP [263]	17969.93	33.9700
DE [265]	17959.61	2.69
DEC [265]	17960.11	2.74
CDE-SQP [265]	17938.95	0.5000
MBFA	17845.82	0.6361

4.6.4 Case Study 4: 40-Generator System

In this case study the number of generation units is 40 with a total demand of 10500 MW with the valve-point effects considered. The system data is presented in Table 4.22 and also available in [264]and [266].

Table 4.22 Data for the 40-generator system of Case Study 4

Unit	Parameter							Unit	Parameter						
	a_i	b_i	c_i	e_i	f_i	P_{gi}^{min} MW	P_{gi}^{max} MW		a_i	b_i	c_i	e_i	f_i	P_{gi}^{min} MW	P_{gi}^{max} MW
1	0.00690	6.73	94.705	100	0.084	36	114	21	0.00298	6.63	785.96	300	0.035	254	550
2	0.00690	6.73	94.705	100	0.084	36	114	22	0.00298	6.63	785.96	300	0.035	254	550
3	0.02028	7.07	309.54	100	0.084	60	120	23	0.00284	6.66	794.53	300	0.035	254	550
4	0.00942	8.18	369.03	150	0.063	80	190	24	0.00284	6.66	794.53	300	0.035	254	550
5	0.01140	5.35	148.89	120	0.077	47	97	25	0.00277	7.10	801.32	300	0.035	254	550
6	0.01142	8.05	222.33	100	0.084	68	140	26	0.00277	7.10	801.32	300	0.035	254	550
7	0.00357	8.03	278.71	200	0.042	110	300	27	0.52124	3.33	1055.10	120	0.077	10	150
8	0.00492	6.99	391.98	200	0.042	135	300	28	0.52124	3.33	1055.10	120	0.077	10	150
9	0.00573	6.60	455.76	200	0.042	135	300	29	0.52124	3.33	1055.10	120	0.077	10	150
10	0.00605	12.90	722.82	200	0.042	130	300	30	0.01140	5.35	148.89	120	0.077	47	97
11	0.00515	12.90	635.20	200	0.042	94	375	31	0.00160	6.43	222.92	150	0.063	60	190
12	0.00569	12.80	654.69	200	0.042	94	376	32	0.00160	6.43	222.92	150	0.063	60	190
13	0.00421	12.50	913.40	300	0.035	125	500	33	0.00160	6.43	222.92	150	0.063	60	190
14	0.00752	8.84	1760.40	300	0.035	125	500	34	0.00010	8.95	107.87	200	0.042	90	200
15	0.00708	9.15	1728.30	300	0.035	125	500	35	0.00010	8.62	116.58	200	0.042	90	200
16	0.00708	9.15	1728.30	300	0.035	125	500	36	0.00010	8.62	116.58	200	0.042	90	200
17	0.00313	7.97	647.85	300	0.035	220	500	37	0.01610	5.88	307.45	80	0.098	25	110
18	0.00313	7.95	649.69	300	0.035	220	500	38	0.01610	5.88	307.45	80	0.098	25	110
19	0.00313	7.97	647.83	300	0.035	242	550	39	0.01610	5.88	307.45	80	0.098	25	110
20	0.00313	7.97	647.81	300	0.035	242	550	40	0.00313	7.97	647.83	300	0.035	242	550

The MBFA is successfully applied to find the optimal power dispatch for this system. The optimal generation level of each unit is shown in Table 4.23.

Table 4.23 Optimal generation for the 40-generator system of Case Study 4

Unit	P_{gi}^{min} MW	P_{gi}^{max} MW	Optimal Generation MW	Unit	P_{gi}^{min} MW	P_{gi}^{max} MW	Optimal Generation MW
1	36	114	106.4415	21	254	550	542.9079
2	36	114	112.2997	22	254	550	521.1754
3	60	120	91.3844	23	254	550	528.7296
4	80	190	164.7806	24	254	550	548.4591
5	47	97	97.0000	25	254	550	512.8029
6	68	140	140.0000	26	254	550	532.5020
7	110	300	297.9833	27	10	150	10.0000
8	135	300	298.7559	28	10	150	10.0000
9	135	300	298.7681	29	10	150	10.0000
10	130	300	130.0000	30	47	97	84.4172
11	94	375	154.8044	31	60	190	180.2997
12	94	376	94.6298	32	60	190	189.3172
13	125	500	219.0148	33	60	190	181.2538
14	125	500	392.8003	34	90	200	178.3303
15	125	500	307.2984	35	90	200	196.1330
16	125	500	301.1605	36	90	200	200.0000
17	220	500	491.4072	37	25	110	110.0000
18	220	500	498.3393	38	25	110	110.0000
19	242	550	511.7271	39	25	110	110.0000
20	242	550	520.2939	40	242	550	514.7826

Statistical figures regarding the cost obtained is shown in Table 4.24 and compared to those obtained using the methods listed in Case Study 3 above in addition to the Modified PSO (MPSO) method presented in [266]. The comparison is illustrated in Table 4.25. The minimum cost associated with the proposed MBFA is 119898.197 \$/h which is less than those given by the other methods shown in Table 4.25. The annual amount of reduction in cost gained by applying the proposed method in this case is 16,151,512.80$. This amount is computed based on the difference between the cost achieved by the proposed method and the lowest cost given by the other methods shown in the table.

Table 4.24 Results of 30 runs (40-generator system with valve-point effects)

Cost ($/h)					Average time (sec)
Min	Max	Average	STD	Range	
119898.20	121368.13	120294.37	580.16	1469.93	6.4163

Table 4.25 Comparison of the results (13-generator system with valve-point effects)

Method	Total Cost ($/h)	Average Time (sec)
EP [264]	122624.35	1167.35
PSO [263]	122930.45	933.39
MPSO [266]	122252.27	--------
HEP-SQP [263]	122323.97	997.73
HPSO-SQP [263]	122094.67	733.97
DE [265]	121900.88	5.12
DEC [265]	121815.80	5.01
CDE-SQP [265]	121741.98	14.26
MBFA	119898.20	6.42

This case shows that the proposed MBFA performs well in solving the ED problem in spite of the high dimensionality of the search hyperspace and the non-smoothness of the objective function due to the valve-pint effects. The descriptive statistics of Table 4.24 show that the standard deviation is 580.16 $/h and the range between the minimum and maximum cost is 1469.93 $/h.

4.7 Summary

In this chapter the ED problem is discussed and modeled. The MBFA is applied to determine the optimal ED for various generation system configurations. The ED problem treated in this chapter was initially solved using the simple power balance model which neglected transmission losses. Then it was followed by the formulation of the active power losses using the transmission loss formula. Valve-point effects were also discussed and included in the problem formulation. Simulation results have demonstrated the effectiveness and consistency of the MBFA in finding an optimal or near-optimal solution. Comparisons with other deterministic and heuristic methods has shown that the proposed algorithm has achieved significantly better results in most of the test cases and no less than better in the others. The ED case studies discussed in this chapter are also discussed in [267] and [268].

CHAPTER 5 SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING

5.1 INTRODUCTION

The objective of hydro-thermal scheduling is to determine the generation level for each committed hydro and thermal unit in such a way that the total operating cost is minimized while satisfying various operational constraints [2]. In large-scale hydro-thermal generation systems, it is indispensable to operate thermal and hydro plants integrated in the same grid in order to achieve the optimal economic operation. Although the capital cost of hydro-electric plants is high, their operating cost does not depend on the output power. In contrast, the capital cost of the thermal plants is lower but their operating cost varies with the output power. In addition, while the starting and speed of response of thermal units are slow, hydro-electric plants can respond and start quickly and can handle fluctuating loads with high reliability. For these complementary characteristics of thermal and hydro-electric plants, the integrated operation of these plants is both economic and convenient practice. In contrast to thermal power production, there is no fuel cost associated with hydro-electric generation. However, fixed charges are accounted for regardless of the amount of the hydro power produced. Therefore, it is essential to use up the entire amount of water available over a planning period of time. In addition to generating electric power, hydro-electric plants must meet certain obligations as the reservoirs are multipurpose in most cases. A maximum forebay elevation, for instance, must not be exceeded due to the flooding considerations. In addition, to meet irrigational and navigational commitments, a minimum reservoir discharge and spillage must be observed. Hydro-electric systems can be differentiated depending on various aspects such as the number of hydro plants and, their operating characteristics and location. The hydro plants located on different streams have quite different characteristics from those on the same stream where water transport delay can be an important factor. The influence of the upstream reservoir on the operation of the next downstream one is greatly significant. On the other hand, the effect of the downstream plant on the tail water elevation and net head can also influence the upstream plant [3].

In this chapter, generation scheduling of electrical power systems that contain both thermal and hydro plants is studied. The hydro-thermal generation scheduling problem is different from the all-thermal one discussed in Chapter 4. The economic dispatch of all-thermal generation problem is a static optimization process which allocates generation resources on an instantaneous basis [269]. The MBFA presented in Chapter 3 is applied in the present chapter to solve the hydro-thermal generation problem. Both hydraulically isolated plants and plants on the same stream are considered. In the first part, fixed-head and variable-head plants are treated. Several case studies are presented taking into consideration power transmission losses and valve-point effects. In the rest of this section, various issues associated with hydro-electric plants are introduced and discussed.

5.1.1 Hydro-electric Plant Installation Types

Hydro-electric power plants are classified into two types; pumped storage and conventional. The latter is further categorized into storage and run-of-river [3].

5.1.1.1 Storage Plants

Storage plants have reservoirs of significant storage capacity. In these plants water is stored during low load demand periods and utilized during peak load periods. Generation scheduling of hydro-thermal systems with storage plants is the subject of this chapter.

5.1.1.2 Run-of-River Plants

This type of plants can only use water when it becomes available because they have no or little storage capacity. Consequently, when water is spilled over it is not utilized. Run-of-river plants are located in the stream or alongside, and in such case it is referred to as canal-type power plant. The output of these plants is modeled as a negative load in economic operation studies.

5.1.1.3 Pumped-Storage Plants

Pumped-storage plants have upper and lower reservoirs in their models. Water is pumped to the upper reservoir when the load demand is low. During high demand periods, water is released to the lower reservoir to be used by the hydro turbine. These plants may use independent turbines and pumps or reversible pump-turbine units. The operation of the pumped-storage plant continues until the added cost due to pumping exceeds the savings in thermal operating costs due to what is known as the peak shaving operations [2].

5.1.2 Plant Location

Hydro-thermal plants can be classified into three types depending on their location. They can be hydraulically isolated as they are located on different streams, hydraulically coupled on the same stream or cascaded in a multi-chain plant configuration. The following is a brief explanation on each of these three categories.

5.1.2.1 Hydro Plants on Different Streams

Hydro plants on different streams are hydraulically isolated as there is no coupling between them except through the electric network. Therefore, their operation is hydraulically independent as they are not located on the same stream. Figure 5.1 is a schematic diagram of typical hydro plants on different streams.

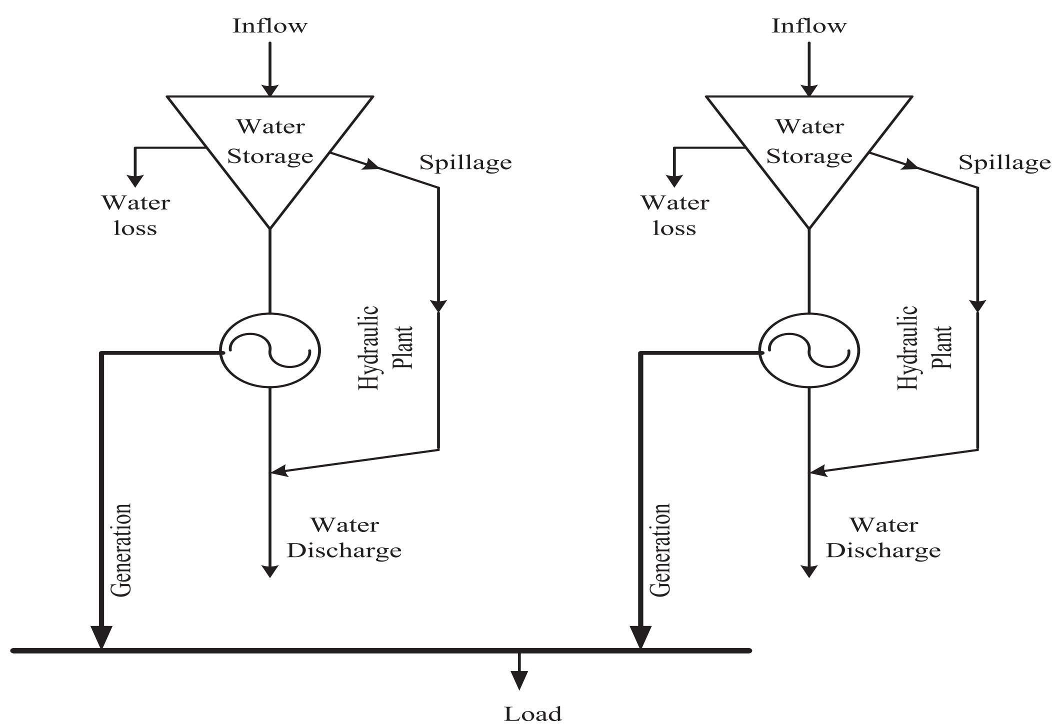

Figure 5.1 Hydro plants not on the same stream

5.1.2.2 Hydro Plants on the Same Stream

Hydro plants located on the same stream are also called derail or cascaded plants. In this plant arrangement, the downstream plant is significantly influenced by the immediate upstream one which in turn is affected by the tail water elevation and effective head of the immediate downstream plant. A typical cascaded hydro plant configuration is illustrated in Figure 5.2.

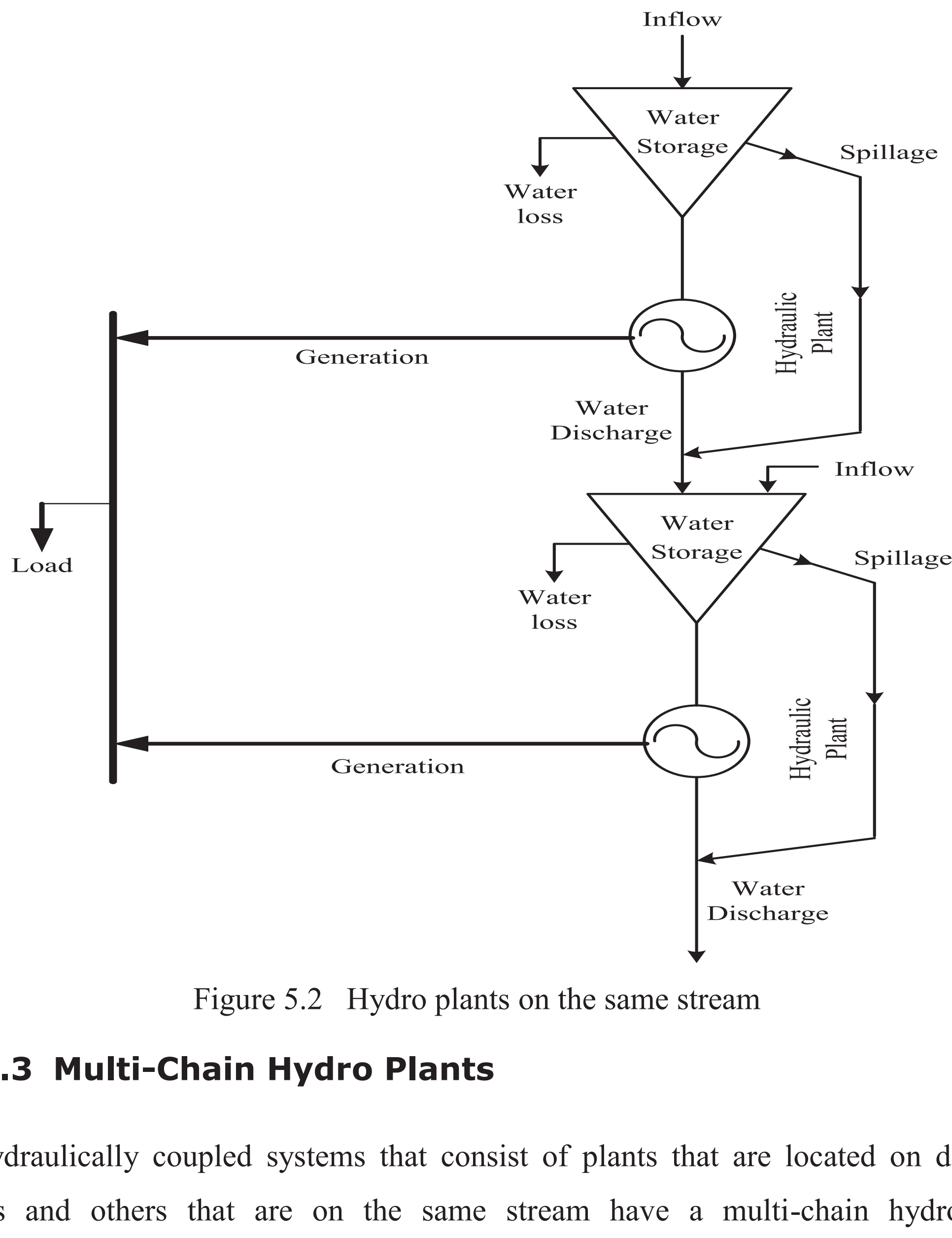

Figure 5.2 Hydro plants on the same stream

5.1.2.3 Multi-Chain Hydro Plants

Hydraulically coupled systems that consist of plants that are located on different streams and others that are on the same stream have a multi-chain hydro plant arrangement. Figure 5.3 shows a typical configuration of a multi-chain hydro plant system.

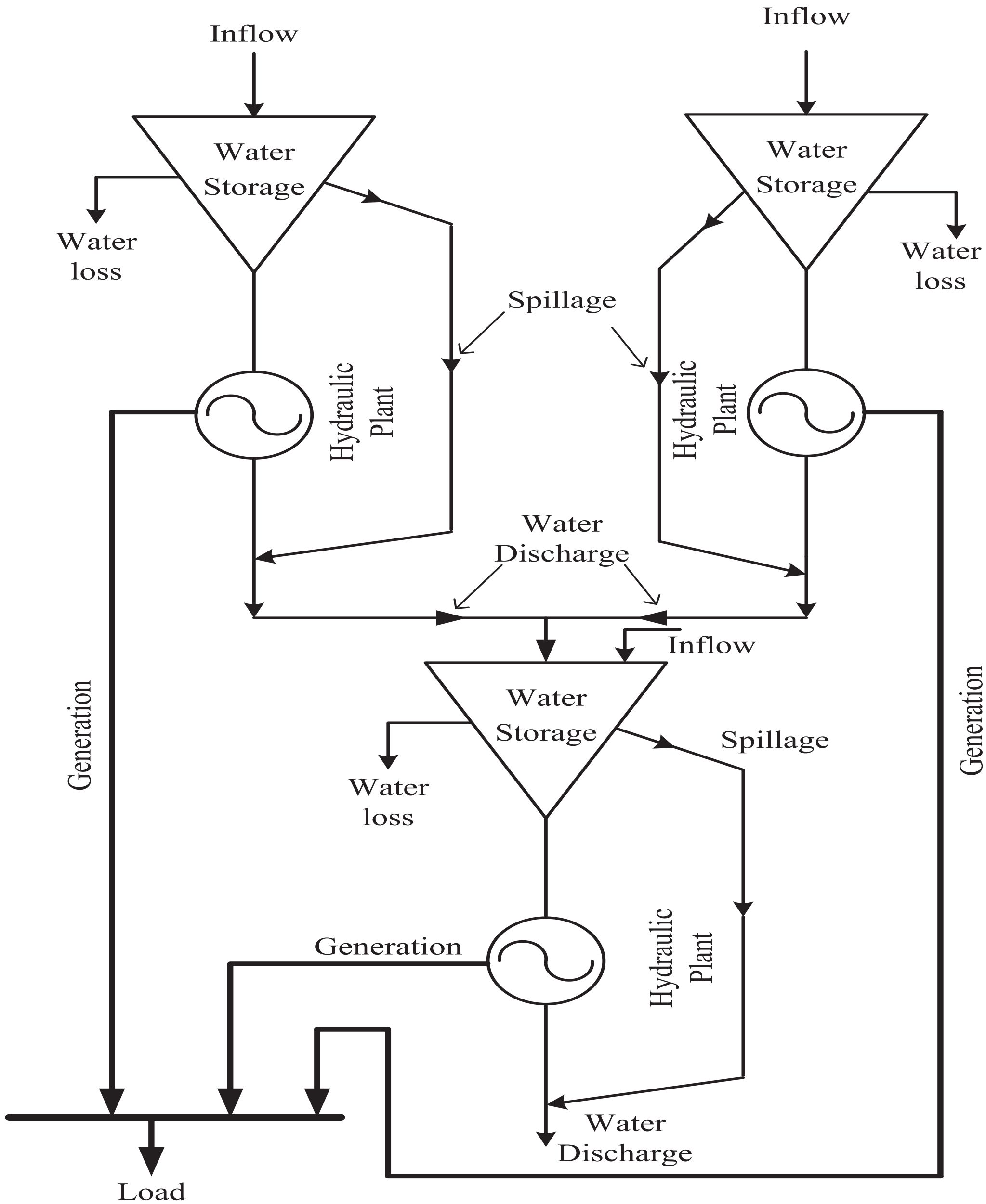

Figure 5.3 Multi-chain hydro plants

5.1.3 Hydro Turbine Models

Hydro turbines can be classified into two general types. These are; reaction type and impulse type [3]. In the first type, water under pressure enters the turbine after it is partly converted into velocity. The most commonly used turbines of this type are the Francis wheel, the Kaplan wheel and propeller wheel. In the second type, water under pressure is entirely converted into velocity.

The output active power of a hydro turbine is expressed in terms of rate of water discharge and the effective head as follows:

$$P_H = (qh/102)\eta_t \eta_G \tag{5.1}$$

where P_H : output active hydro power generation (MW)

q : rate of water discharge $(m^3/\sec)$

h : effective water head (m)

η_t : turbine efficiency

η_G : generator efficiency

Due to the diversity of installation characteristics, there exist several different models. All these models are principally based on Equation (5.1). Following are the most commonly used models [3].

5.1.3.1 Glimn-Kirchmayer Model

This model is the most popular one in which the rate of discharge is mathematically expressed as a bi-quadratic function of the active power and net water head.

$$q = K\psi(h)\phi(P_H) \tag{5.2}$$

$$\psi(h) = a_0 + a_1 h + a_2 h^2 \tag{5.3}$$

$$\phi(P_H) = b_0 + b_1 P_H + b_2 P_H^2 \tag{5.4}$$

where K is a constant of proportionality.

5.1.3.2 Hildebrand Model

This model is a more generalized form than the Glimn-Kirchmayer model. The rate of discharge of this model is given by:

$$q = \sum_{i=0}^{k}\sum_{i=0}^{l} C_{ij} P_H^i h^j \tag{5.5}$$

where C_{ij} : hydro turbine model coefficients

k : maximum exponent

l : maximum exponent

5.1.3.3 Hamilton-Lamonts Model

The mathematical representation of rate discharge of this model is given by:

$$q = (a_0 + a_1 h + a_2 h^2)(b_0 + b_1 P_H + b_2 P_H^2) / h \tag{5.6}$$

5.1.3.4 Arvanitidis-Rosing Model

Unlike the previous models that describe the rate of water discharge in terms of net head and power generation, this model defines the output power as an exponential variation of net head and reservoir storage:

$$P_H = qh(\beta_R - e^{-\alpha_R A\,(h-h_0)}) \tag{5.7}$$

where A : area of the reservoir (m^2)

h_0 : minimum water head (m)

α_R, β_R : model coefficients

5.1.4 Long-Term Hydro-Thermal Scheduling Problem

Long-term hydro-thermal generation scheduling typically ranges from 1 week to 1 year or several years [2]. This long-term scheduling problem consists of the long-term water availability forecasting and the scheduling of water releases from the reservoirs. It also involves meteorological and statistical analysis related to the availability of water over several seasons. Long-term scheduling also involves the optimization of policies regarding various unknowns such as load forecasting, generating unit availability and water inflows. In general, the long-term hydro-thermal scheduling problem can be classified into three categories depending on the plant location. The hydro plants of the first group are located on different streams so that they have separate reservoirs. The second category is called the cascaded hydro plants where these plants are located on the same stream. Multi-chain systems, which are the third group, have their hydro plants located on different streams.

The long-term hydro-thermal scheduling problem is out of the scope of this thesis which only treats the short-term one. A wide range of optimization techniques has been applied to treat the long-term hydro-thermal scheduling and reported in literature [270-273].

5.1.5 Short-Term Hydro-Thermal Scheduling Problem

The scheduling period of the short-term hydro-thermal problem can range from 1 day to 1 week [2, 3]. The solution to the short-term problem is to determine the hour-by-hour scheduling of all available generation in order to obtain the optimal economic production cost over the scheduling period. In this problem, the available generating units and the load demand for each scheduling interval as well as the water inflow are assumed known. In addition, the information about water availability and reservoir levels at the start and end of the scheduling period are known. Depending on the head of the reservoir, the short-term problem can be categorized into two main groups which are the fixed-head and variable-head. The first group is associated with plants with large capacity reservoirs while variable-head reservoirs have limited amounts of water. A comprehensive literature review of the various optimization methods applied to solve this problem is presented in Chapter 2 and in [214] as well. The short-term hydro-thermal scheduling problem is discussed extensively in the rest of this chapter as it is the main focus of this thesis.

5.2 Short-Term Fixed-Head Hydro-Thermal Generation Scheduling

The problem considered in this section is the short-term optimal economic operation of hydro-thermal systems with fixed-head reservoirs. These reservoirs are assumed to be large enough so that they have large amounts of water. The generation system treated consists of both hydro and thermal generating units. The objective of the short-term hydro-thermal optimization problem is to minimize the total operating cost by minimizing the fuel cost associated with the thermal electric power generation. This minimization of the fuel cost objective function is subject to various operational thermal and hydraulic constraints.

The hydro-thermal generation system consists of N_g thermal generating plants and M_H hydro-electric plants. In particular, the solution to the problem is to determine the active power generation level of each of the hydro and thermal plants over the scheduling period T .

5.2.1 Thermal Model and Objective Function

As stated above, the short-term hydro-thermal optimization is to minimize the total system operating cost represented by the fuel cost of the thermal units. Mathematically, this objective function to be minimized is expressed as follows [2, 3]:

$$F_T = \int_0^T \sum_{i=1}^{N_g} F_i \left(P_{gi}(t) \right) dt \tag{5.8}$$

where $P_{gi}(t)$: power generation of thermal unit i at time t

$F_i(P_{gi}(t))$: operating cost for thermal unit i at time t

N_g : number of thermal generating units

T : scheduling time period

The fuel cost function, $F_i(P_{gi}(t))$, of the i^{th} thermal generating unit at time t is expressed as the following:

$$F_i(P_{gi}(t)) = a_i P_{gi}^2(t) + b_i P_{gi}(t) + c_i \tag{5.9}$$

where a_i ,b_i and c_i are the cost coefficients of the i^{th} thermal generating unit.

5.2.2 Hydro Model

As mentioned above, there is no fuel cost associated with the hydro power generation. The input-output characteristics of a hydro-electric generating unit is formulated as a water discharge rate in terms of its reservoir's effective water head and the output active power as defined by the Glimn-Kirchmayer model [269, 274].

$$q_j(t) = K\psi(h_j)\phi(P_{Hj}(t)) \tag{5.10}$$

where $q_j(t)$: water discharge rate for the reservoir j at time t

$P_{Hj}(t)$: power generation of hydro unit j at time t

ψ, ϕ : independent functions as defined in Equations (5.3) and (5.4)

K : constant of proportionality.

For a fixed-head reservoir, where the effective net head is assumed constant, the function $\psi(h_j)$ is constant and hence, Equation (5.10) becomes as follows:

$$q_j(t) = K^{'} \phi(P_{Hj}(t)) \tag{5.11}$$

For the scheduling period, the amount of water available for each hydro plant is limited by a pre-specified quantity V_j :

$$\int_0^T q_j(t)dt = V_j \tag{5.12}$$

5.2.3 Constraints

The objective function represented by Equation (5.8) is subject to a number of constraints as follows:

- Load balance equation: The total power generation must meet the total load demand over the scheduling period $P_D(t)$ including the transmission power losses $P_L(t)$. This is represented by the following equality constraint:

$$\sum_{i=1}^{N_g} P_{gi}(t) + \sum_{j=1}^{M_H} P_{Hj}(t) - P_D(t) - P_L(t) = 0 \tag{5.13}$$

- Thermal and hydro generation capacity limits: The maximum and minimum power of the thermal and hydro generating plants are expressed as the following inequality boundary constraints:

$$P_{gi}(t)^{\min} \le P_{gi}(t) \le P_{gi}(t)^{\max} \tag{5.14}$$

$$P_{Hj}(t)^{\min} \le P_{Hj}(t) \le P_{Hj}(t)^{\max} \tag{5.15}$$

where $P_{gi}^{\min}$: minimum power generation for thermal generating unit i

$P_{gi}^{\max}$: maximum power generation for thermal generating unit i

$P_{Hj}^{\min}$: minimum power generation for hydro generating unit j

$P_{Hj}^{\max}$: maximum power generation for hydro generating unit j

5.2.4 Transmission Losses

The loss formulas defined by Equations (4.14), (4.15) and (4.16) are applied to model the transmission network losses. Accordingly, the Kron's *B*-coefficients loss formula is expressed as follows:

$$P_L(t) = \sum_{i=1}^{N_g+M_H} \sum_{j=1}^{N_g+M_H} P_i(t) B_{ij} P_j(t) + \sum_{i=1}^{N_g} B_{i0} P_i(t) + B_{00} \tag{5.16}$$

where $P_i(t), P_j(t)$ can be either the power generation of hydro or thermo plants and the parameters B_{ij} are the loss coefficients or *B*-coefficients.

5.2.5 Discrete Formulation of the Problem

The scheduling time period is divided into a number of scheduling time intervals and hence, the objective function of Equation (5.8) is expressed in a discrete form as follows:

$$F_T = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k F_i\left(P_{gi_k}\right) \tag{5.17}$$

where P_{gi_k} : power generation of thermal unit i at time interval k

$F_i(P_{gi_k})$: operating cost for thermal unit i at time interval k

N_k : number scheduling time intervals

n_k : number of hours in scheduling time interval k

Accordingly, the fuel cost function defined by Equation (5.9) is rewritten as follows:

$$F_i(P_{gi_k}) = a_i P_{gi_k}^2 + b_i P_{gi_k} + c_i \tag{5.18}$$

The minimization of this objective function is subject to the following equality and inequality constraints that are hydro and thermal:

- Load balance equation:

$$\sum_{i=1}^{N_g} P_{gi_k} + \sum_{j=1}^{M_H} P_{Hj_k} - P_{D_k} - P_{L_k} = 0 \tag{5.19}$$

where P_{Hj_k} : power generation of hydro unit j at time interval k

P_{D_k} : total load demand during the time interval k

P_{L_k} : total transmission power losses during the time interval k

The transmission power losses are given by the following redefined loss formula:

$$P_{L_k} = \sum_{i=1}^{N_g+M_H} \sum_{j=1}^{N_g+M_H} P_{i_k} B_{ij} P_{j_k} + \sum_{i=1}^{N_g} B_{i0} P_{i_k} + B_{00} \tag{5.20}$$

- Generation boundary condition:

$$P_{gi_k}^{\min} \leq P_{gi_k} \leq P_{gi_k}^{\max} \tag{5.21}$$

$$P_{Hj_k}^{\min} \leq P_{Hj_k} \leq P_{Hj_k}^{\max} \tag{5.22}$$

- Water availability limits:

$$\sum_{k=1}^{N_k} n_k q_{j_k} = V_j \tag{5.23}$$

where q_{j_k} is the water discharge rate of the hydro plant j at the time interval k. The characteristic equation of the discharge rate q_{j_k} can be modeled as follows [275]:

$$q_{j_k} = \alpha_j P_{Hj_k}^2 + \beta_j P_{Hj_k} + \gamma_j \tag{5.24}$$

where α_j, β_j *and* γ_j are the discharge rate coefficients for the j^{th} hydro plant.

5.2.6 Case Study 1: One Thermal and One Hydro Plant (1 Day)

The system in this case study is a well-known example adapted from [2]. This system consists of a hydro plant and an equivalent thermal generating plant with the following characteristics for the equivalent thermal system:

$$F_1(P_{g1}(t)) = 0.00184 P_{g1}^2(t) + 9.2 P_{g1}(t) + 575 \quad \$/h \tag{5.25}$$

$$150MW \leq P_{g1}(t) \leq 1500MW \tag{5.26}$$

The water discharge rate is expressed as:

- *for* $0 \leq P_{H1}(t) \leq 1000MW$

$$q_1(t) = 330 + 4.97 P_{H1}(t) \, acre.ft/h \tag{5.27}$$

- *and for* $1000 \leq P_{H1}(t) \leq 1100MW$

$$q_1(t) = 5300 + 12(P_{H1}(t) - 1000) + 0.05(P_{H1}(t) - 1000)^2 \, acre.ft/h \tag{5.28}$$

The thermal plant is close enough to the load center so that the transmission power losses are only associated with the hydro plant and expressed as follows:

$$P_L(t) = 0.00008 P_{H1}^2(t) \tag{5.29}$$

The scheduling period is 1 day divided into two intervals of 12 hours each. The total load demand to be supplied by the hydro-thermal generation system during the 12-hour intervals is as follows:

$$\begin{aligned} &\text{12 am-12 pm}: \; P_D(t) = 1200MW \\ &\text{12 pm-12 am}: \; P_D(t) = 1500MW \end{aligned} \tag{5.30}$$

The water reservoir of the hydro plant is limited to a drawdown of 100,000 *acre-ft* over the scheduling period:

$$\int_0^T q_1(t)dt = 100{,}000 \quad acre.f \tag{5.31}$$

The proposed MBFA is applied to solve this case problem and results are compared to those obtained by the Lambda-Gamma Iteration Method (LGIM) used in [2]. Table 5.1 and Table 5.2 show the results and the comparison.

Table 5.1 One thermal and one hydro system (1 day)

		Method	
Interval	Variable	LGIM [2]	MBF
12am–12pm	P_{g1} (MW)	567.40	565.89
	P_{H1} (MW)	668.30	670.03
	q_1 (acre-ft/h)	3651.50	3660.00
12pm–12am	P_{g1} (MW)	685.70	687.17
	P_{H1} (MW)	875.60	873.93
	q_1 (acre-ft/h)	4681.70	4673.40
Total Cost ($)		169,630	169,630

Table 5.2 Objective function statistical data for Case study 1 (1 day)

Cost ($)			Average time (sec)
Min	Max	Average	
169630.13	169631.25	169630.90	7.2356

5.2.7 Case Study 2: One Thermal and One Hydro Plant (3 Days)

In this case the same system of the previous case study is considered with a scheduling period of three days of two intervals each. The load demand pattern for the six intervals is as follows:

$$
\begin{array}{lll}
\text{Day 1:} & \text{12 am-12 pm}: & P_D(t) = 1200MW \\
 & \text{12 pm-12 am}: & P_D(t) = 1500MW \\
\text{Day 2:} & \text{12 am-12 pm}: & P_D(t) = 1100MW \\
 & \text{12 pm-12 am}: & P_D(t) = 1800MW \\
\text{Day 3:} & \text{12 am-12 pm}: & P_D(t) = 950MW \\
 & \text{12 pm-12 am}: & P_D(t) = 1300MW
\end{array} \tag{5.32}
$$

The starting volume of the water in the plant reservoir is 100,000 *acre·ft* and must be 60.000 *acre·ft* at the end. The reservoir volume limits are as follows:

$$60,000 \;\; acre \bullet ft \leq V \;\leq 120,000 \;\; acre \bullet ft \tag{5.33}$$

The flow rate into the reservoir is constant over the scheduling period and equals to 2000 *acre-ft/h*.

The optimal power generation schedule and the corresponding reservoir volume and discharge rates for this system are obtained by the proposed MBFA algorithm as shown in Table 5.3.

Table 5.3 One thermal and one hydro system (3 days)

Interval	P_{H1} (MW)	P_{g1} (MW)	Volume V (*acre-ft*)	Discharge rate q_1 *(acre-ft/h)*
1	897.511	303.967	101917.946	1840.717
2	897.978	604.388	85805.643	3333.81
3	894.201	201.555	93207.929	1331.729
4	897.555	903.962	60029.223	4822.689
5	782.811	164.573	70670.404	1147.929
6	792.915	515.237	60080.647	2890.729

Results show that the proposed algorithm has achieved significantly good results in solving the problem. The cost obtained is \$709,837.93 as shown in Table 5.4 which also presents some statistical data about the algorithm convergence characteristics.

Table 5.4 Cost obtained for Case Study 2 (3 days)

Cost ($)			Average time (sec)
Min	Max	Average	
709,837.93	710,113.86	709,877.56	12.654

The cost obtained by the proposed algorithm is compared with those of the gradient search (GS) method [2], improved fast evolutionary programming (IFEP) technique, genetic algorithm (GA) [108], simulating annealing (SA) [276] and particle swarm optimization (PSO) [97]. Table 5.5 demonstrates this comparison and shows that the MBFA outperforms the other deterministic and heuristic methods.

Table 5.5 Comparison of the cost obtained Case Study 2 (3 days)

Method	Cost ($)
GS [2]	709,877.38
IFEP [108]	709,862.05
GA [108]	709,863.56
SA [276]	709,874.36
PSO [97]	709,862.05
MBFA	709,837.93

5.2.8 Case Study 3: One Thermal and Two Hydro Plants

This system, which was studied in [275], consists of three generation units; one is thermal and two are hydro. The characteristics of the thermal plant are given by:

$$F_1(P_{g1}(t)) = 0.01P_{g1}^2(t) + 3.0P_{g1}(t) + 15 \quad \$/h \tag{5.34}$$

The discharge rates of the two reservoirs in terms of the hydro power produced by the two plants are as the following:

$$q_1(t) = 0.00005P_{H1}^2(t) + 0.03P_{H1}(t) + 0.2M.ft^3/h \tag{5.35}$$

$$q_2(t) = 0.0001P_{H2}^2(t) + 0.06P_{H2}(t) + 0.4M.ft^3/h \tag{5.36}$$

The volume of water available for the first hydro plant is 573.916 $M.ft^3$ and for the second is 803.488 $M.ft^3$.

The loss formula coefficients are given by the following:

$$\mathbf{B} = 10^{-3}\begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.0 & 1.0 & 0.0 \\ 0.0 & 0.0 & 0.5 \end{bmatrix}, \mathbf{B_0} = \begin{bmatrix} 0.0 \\ 0.0 \\ 0.0 \end{bmatrix}, B_{00} = 0.0 \tag{5.37}$$

The scheduling period is 1 day divided into 24 time intervals of 1 hour each. The load demand for each period is given by Table 5.6.

Table 5.6 1 thermal and 2 hydro plants (load demand)

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	30	7	50	13	60	19	55
2	33	8	59	14	61	20	50
3	35	9	61	15	65	21	43
4	38	10	58	16	68	22	33
5	40	11	56	17	71	23	31
6	45	12	57	18	62	24	30

The MBFA is successfully applied to this problem considering the transmission power losses in the load balance equation. The optimal power schedule and the water discharge rates over the scheduling period are tabulated in Table 5.7.

Table 5.7 1 thermal and 2 hydro plants (power and discharge schedule)

Hour	Generation (MW) Thermal	Generation (MW) Hydro Plant1	Generation (MW) Hydro Plant2	$P_L(t)$ (MW)	Discharge rate ($M.ft^3/h$) Plant1	Discharge rate ($M.ft^3/h$) Plant2
1	1.2834	20.2272	8.9355	0.4461	19.067900	21.678300
2	2.0860	21.2321	10.1825	0.5005	19.731800	23.444100
3	2.6276	21.9053	11.0139	0.5468	20.230400	24.626900
4	3.4250	22.9147	12.2545	0.5943	20.978700	26.407200
5	3.9619	23.5910	13.0833	0.6362	21.478900	27.599700
6	5.3104	25.2776	15.1652	0.7533	22.732300	30.598600
7	6.6725	26.9518	17.2464	0.8707	23.990500	33.621700
8	9.1301	29.9701	21.0057	1.1059	26.269400	39.128000
9	9.6860	30.6418	21.8428	1.1705	26.777700	40.362700
10	8.8612	29.6443	20.5858	1.0913	26.015600	38.511900
11	8.3172	28.9731	19.7566	1.0469	25.508100	37.283700
12	8.5862	29.3017	20.1621	1.0500	25.761900	37.897400
13	9.4122	30.3160	21.4264	1.1546	26.523100	39.745000
14	9.6895	30.6455	21.8440	1.1790	26.777700	40.362700
15	10.7912	31.9826	23.5176	1.2913	27.797600	42.844300
16	11.6212	32.9949	24.7763	1.3923	28.563700	44.716200
17	12.4643	33.9942	26.0307	1.4891	29.332200	46.597900
18	9.9619	30.9844	22.2659	1.2122	27.032200	40.981300
19	8.0315	28.6362	19.3316	0.9993	25.254400	36.670800
20	6.6707	26.9503	17.2475	0.8685	23.990500	33.621700
21	4.7729	24.6075	14.3316	0.7120	22.230400	29.395500
22	2.0830	21.2381	10.1861	0.5071	19.731800	23.444100
23	1.5548	20.5550	9.3564	0.4662	19.234900	22.266100
24	1.2808	20.2231	8.9329	0.4368	18.986800	21.678300

The minimum cost obtained is \$ 848.25 as shown in Table 5.8. The CPU time required for the convergence is 11.9658 seconds as shown in the table. The load demand curve and the optimal power generation schedule are illustrated in Figure 5.4.

Table 5.8 Cost obtained for Case Study 3 (24 hours)

Cost (\$)			Average time (sec)
Min	Max	Average	
848.25	849.90	848.85	11.9658

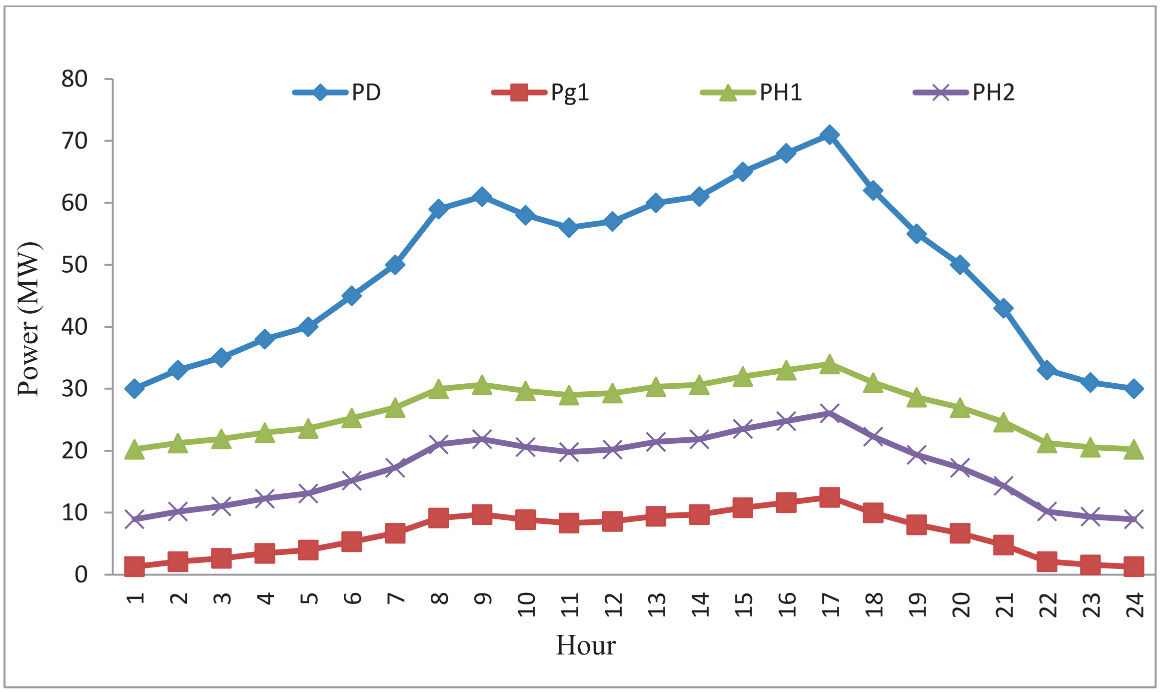

Figure 5.4 Load curve and optimal solution for Case Study 3

5.2.9 Case Study 4: Three Thermal and One Hydro Plants

The hydro-thermal generation system considered in this study consists of one hydro-electric plant and three thermal generating units. The characteristic functions of the thermal plants are defined as follows [1]:

$$F_1(P_{g1}(t)) = 0.01P_{g1}^2(t) + 0.1P_{g1}(t) + 100 \quad \$/h \tag{5.38}$$

$$F_2(P_{g2}(t)) = 0.02P_{g2}^2(t) + 0.1P_{g2}(t) + 120 \quad \$/h \tag{5.39}$$

$$F_3(P_{g3}(t)) = 0.01P_{g3}^2(t) + 0.2P_{g3}(t) + 150 \quad \$/h \tag{5.40}$$

The water discharge rate of the hydro plant as a function of the hydro output power is given by:

$$q_1(t) = 0.00004864 P_{H1}^2(t) + 0.01621 P_{H1}(t) + 0.1135 \, acre.ft/h \qquad (5.41)$$

The boundary condition of the problem is defined by the upper and lower limits of the generation capacity of the four plants that are given by:

$$50MW \le P_{g1}(t) \le 200MW \qquad (5.42)$$

$$40MW \le P_{g2}(t) \le 170MW \qquad (5.43)$$

$$30MW \le P_{g3}(t) \le 215MW \qquad (5.44)$$

$$10MW \le P_{H1}(t) \le 100MW \qquad (5.45)$$

The *B*-matrix for the loss coefficients of the transmission system are as follows:

$$\mathbf{B} = 10^{-3} \begin{bmatrix} 0.50 & 0.05 & 0.20 & 0.03 \\ 0.05 & 0.04 & 0.18 & -0.11 \\ 0.20 & 0.18 & 0.50 & -0.12 \\ 0.03 & -0.11 & -0.12 & 0.23 \end{bmatrix} \qquad (5.46)$$

The load demand for each scheduling interval is given by Table 5.9. The amount of water available in the reservoir is limited to 16 200 $acre.ft$.

Table 5.9 3 thermal and 1 hydro plants (load demand)

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	175	7	390	13	565	19	375
2	190	8	410	14	540	20	340
3	220	9	440	15	500	21	300
4	280	10	475	16	450	22	250
5	320	11	525	17	425	23	200
6	360	12	550	18	400	24	180

The resultant optimal power schedule that meets the total load demand for each scheduling time interval including the transmission power losses is shown in Table 5.10. The table also shows the water discharge rate of the hydro plant over the 24 hour scheduling period.

Table 5.10 3 thermal and 1 hydro plants (power and discharge schedule)

Hour	Thermal Generation (MW)			Hydro Gen. (MW)	$P_L(t)$ (MW)	Discharge rate (*acre-ft/h*)
	Plant1	Plant2	Plant3			
1	67.394	40.659	63.893	10.000	6.946	280506.765
2	76.899	41.481	70.763	10.000	9.143	280506.765
3	89.211	49.078	83.355	10.000	11.643	280506.765
4	115.432	66.469	109.262	10.000	21.162	280506.765
5	133.830	77.125	126.346	10.000	27.301	280506.765
6	148.413	88.402	140.954	17.576	35.345	418328.008
7	155.803	94.309	148.155	29.615	37.881	638841.997
8	160.319	98.585	153.949	37.881	40.734	795309.643
9	168.177	104.507	161.351	49.552	43.587	1045820.020
10	177.255	111.248	170.766	64.532	48.800	1361187.452
11	189.249	122.346	183.783	85.547	55.925	1859046.247
12	195.388	127.499	190.597	96.380	59.864	2128932.847
13	199.309	133.160	195.211	99.978	62.658	2298371.904
14	193.277	125.391	187.318	92.820	58.805	2019486.566
15	183.692	116.185	177.659	75.449	52.985	1603590.697
16	170.561	106.568	164.367	54.192	45.688	1133377.045
17	164.205	101.166	157.563	43.488	41.423	918538.049
18	158.570	96.239	151.490	33.521	39.820	716670.463
19	151.070	91.354	144.717	23.628	35.769	526963.576
20	142.889	84.271	135.922	10.787	33.869	280506.765
21	124.336	71.534	117.131	10.000	23.001	280506.765
22	102.597	57.665	96.070	10.000	16.331	280506.765
23	80.624	44.405	75.518	10.000	10.547	280506.765
24	72.577	39.292	66.194	10.000	8.063	280506.765

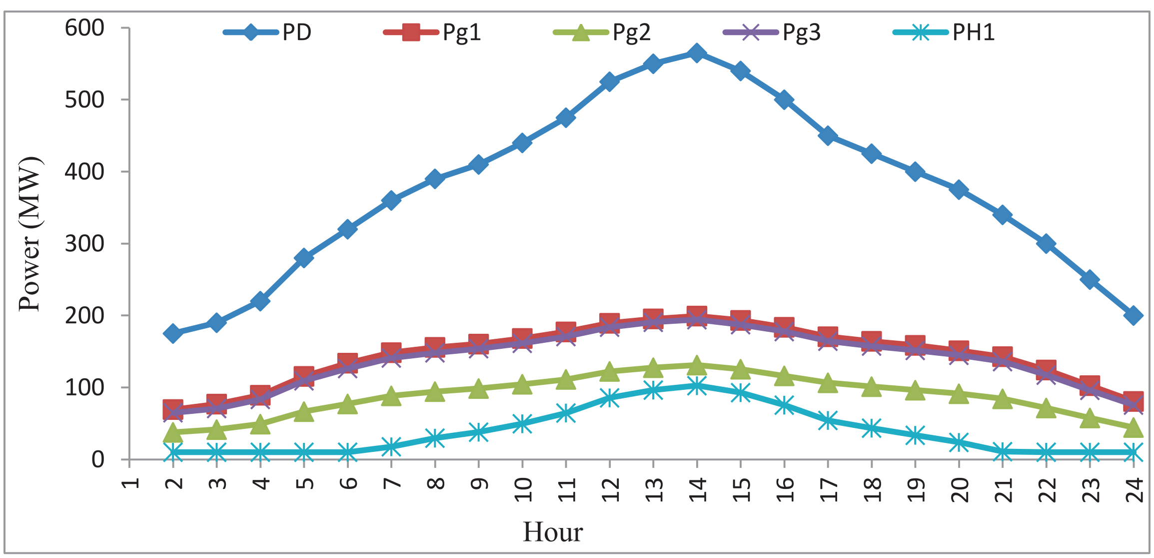

Figure 5.5 Load curve and optimal solution for Case Study 4

The best cost function obtained by the algorithm is \$24267.41 with an average cost of \$24268.25 and a range of \$4.17 between the minimum and maximum cost. These results are shown in Table 5.11. The optimal power schedule and the hourly load demand are shown in Figure 5.5.

Table 5.11 Cost obtained for Case Study 4

Cost (\$)			Average time (sec)
Min	Max	Average	
24267.41	24271.58	24268.25	9.961891

5.3 SHORT-TERM VARIABLE-HEAD HYDRO-THERMAL GENERATION SCHEDULING

In the optimization problem discussed in the previous section, the reservoirs associated with the hydro plants were assumed large enough to have large amounts of water. Based on this assumption, the effective head was assumed constant and hence, the problem was called fixed-head scheduling problem. In the present section, the assumption of fixed-head operation for the plant is relaxed. Practically, for the small capacity reservoirs, the effective head variations cannot be ignored. The hydro-thermal generation system considered for the variable-head scheduling problem consists of N_g thermal generating plants and M_H hydro-electric plants. The solution to the problem is to find the power generation level of each of the hydro and thermal plants over the scheduling period T .

5.3.1 Thermal Model and Objective Function

The objective function to be minimized to solve the variable-head optimization problem is the total fuel cost of the thermal generating units over the scheduling period. The problem is defined as follows [2, 3]:

$$Minimize \qquad F_T = \int_0^T \sum_{i=1}^{N_g} F_i \left(P_{gi}(t)\right) dt \tag{5.47}$$

where $P_{gi}(t)$: power generation of thermal unit i at time t

$F_i(P_{gi}(t))$: operating cost for thermal unit i at time t

N_g	: number of thermal generating units
T	: scheduling time period

The fuel cost function, $F_i(P_{gi}(t))$, of the i^{th} thermal generating unit at time t is given by:

$$F_i(P_{gi}(t)) = a_i P_{gi}^2(t) + b_i P_{gi}(t) + c_i \tag{5.48}$$

where a_i, b_i and c_i are the cost coefficients of the i^{th} thermal generating unit.

5.3.2 Hydro Model

Glimn-Kirchmayer model, [269, 274], can be used to define the discharge rate as follows:

$$q_j(t) = K\psi(h_j)\phi(P_{Hj}(t)) \tag{5.49}$$

where	$q_j(t)$	: water discharge rate for the reservoir j at time t
	$P_{Hj}(t)$	: power generation of hydro unit j at time t
	ψ, ϕ	: independent functions as defined in Equations (5.3) and (5.4)
	K	: constant of proportionality.

For the scheduling period, the amount of water available for each hydro plant is limited by a pre-specified quantity V_j:

$$\int_0^T q_j(t)dt = V_j \tag{5.50}$$

5.3.3 Reservoir Dynamics

A hydro plant j is assumed to have a small capacity vertical-sided reservoir and the water elevation is assumed to be independent of the natural inflow. Considering these assumptions, the reservoir hydro dynamics are obtained and the active net head is determined as follows [3]:

$$h_j(t) = h_j(0) + \frac{1}{S_j}\int_0^t [I_j(t) - q_j(t)]dt \tag{5.51}$$

where	$h_j(0)$	: initial water head of the reservoir j at time $t = 0$

$I_j(t)$: inflow to the reservoir j at time t

S_j : surface area of the assumed vertical-sided reservoir j

$q_j(t)$: water discharge rate for the reservoir j at time t

5.3.4 Constraints

The objective function expressed in Equation (5.47) is subject to the following equality and inequality constraints:

- Load balance equation:

$$\sum_{i=1}^{N_g} P_{gi}(t) + \sum_{j=1}^{M_H} P_{Hj}(t) - P_D(t) - P_L(t) = 0 \tag{5.52}$$

where $P_D(t)$: total load demand over the scheduling period

$P_L(t)$: transmission power losses during the scheduling period

- Thermal and hydro generation capacity limits:

$$P_{gi}(t)^{\min} \le P_{gi}(t) \le P_{gi}(t)^{\max} \tag{5.53}$$

$$P_{Hj}(t)^{\min} \le P_{Hj}(t) \le P_{Hj}(t)^{\max} \tag{5.54}$$

where $P_{gi}^{\min}$: minimum power generation for thermal generating unit i

$P_{gi}^{\max}$: maximum power generation for thermal generating unit i

$P_{Hj}^{\min}$: minimum power generation for hydro generating unit j

$P_{Hj}^{\max}$: maximum power generation for hydro generating unit j

5.3.5 Transmission Losses

The transmission power losses are considered by using the Kron's B-coefficients loss formula as follows:

$$P_L(t) = \sum_{i=1}^{N_g+M_H} \sum_{j=1}^{N_g+M_H} P_i(t) B_{ij} P_j(t) + \sum_{i=1}^{N_g} B_{i0} P_i(t) + B_{00} \tag{5.55}$$

where $P_i(t), P_j(t)$ can be either the power generation of hydro or thermo plants and the parameters B_{ij} are the loss coefficients or *B*-coefficients.

5.3.6 Discrete Formulation of the Problem

The short-term variable-head hydro-thermal generation scheduling problem can be formulated as a discrete optimization problem as follows:

$$Minimize \qquad F_T = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k F_i\left(P_{gi_k}\right) \tag{5.56}$$

where P_{gi_k} : power generation of thermal unit i at time interval k

$F_i(P_{gi_k})$: operating cost for thermal unit i at time interval k

N_k : number of scheduling time intervals

n_k : number of hours in scheduling time interval k

The fuel cost function $F_i(P_{gi_k})$ is given by:

$$F_i(P_{gi_k}) = a_i P_{gi_k}^2 + b_i P_{gi_k} + c_i \tag{5.57}$$

The minimization of this objective function is subject to the following equality and inequality constraints that are hydro and thermal:

- Load balance equation:

$$\sum_{i=1}^{N_g} P_{gi_k} + \sum_{j=1}^{M_H} P_{Hj_k} - P_{D_k} - P_{L_k} = 0 \tag{5.58}$$

where P_{Hj_k} : power generation of hydro unit j at time interval k

P_{D_k} : total load demand during the time interval k

P_{L_k} : total transmission power losses during the time interval k

The transmission power losses are given by the following loss formula:

$$P_{L_k} = \sum_{i=1}^{N_g+M_H} \sum_{j=1}^{N_g+M_H} P_{i_k} B_{ij} P_{j_k} + \sum_{i=1}^{N_g} B_{i0} P_{i_k} + B_{00} \tag{5.59}$$

- Generation boundary condition:

$$P_{gi_k}^{\min} \le P_{gi_k} \le P_{gi_k}^{\max} \tag{5.60}$$

$$P_{Hj_k}^{\min} \le P_{Hj_k} \le P_{Hj_k}^{\max} \tag{5.61}$$

- Water availability limits:

$$\sum_{k=1}^{N_k} n_k q_{j_k} = V_j \tag{5.62}$$

where q_{j_k} is the water discharge rate of the hydro plant j at the time interval k. Water head variation:

$$h_{j_{k+1}} = h_{j_k} + \frac{n_k}{S_j}[I_{j_k} - q_{j_k}] \tag{5.63}$$

where h_{j_k} : water head of the reservoir j during the time interval k

I_{j_k} : inflow to the reservoir j during the time interval k

5.3.7 Case Study 1: Two Thermal and Two Hydro Plants

The system considered in this case study consists of two thermal generating plants and two hydro plants [277]. The characteristics of the thermal plants are given by the following fuel cost functions:

$$F_1(P_{g1_k}) = 0.0025P_{g1_k}^2 + 3.20P_{g1_k} + 25.0 \;\; \$/h \tag{5.64}$$

$$F_2(P_{g2_k}) = 0.0008P_{g2_k}^2 + 3.40P_{g2_k} + 30.0 \;\; \$/h \tag{5.65}$$

The rate discharge variations for each reservoir are expressed using two independent bi-quadratic functions in terms of active generated power and effective net head:

$$\phi(P_{H1_k}) = 0.000216P_{H1_k}^2 + 0.306P_{H1_k} + 0.198 \tag{5.66}$$

$$\phi(P_{H2_k}) = 0.000360P_{H2_k}^2 + 0.612P_{H2_k} + 0.936 \tag{5.67}$$

$$\psi(h_{1_k}) = 0.00001h_{1_k}^2 - 0.0030h_{1_k} + 0.90 \tag{5.68}$$

$$\psi(h_{2_k}) = 0.00002h_{2_k}^2 - 0.0025h_{2_k} + 0.95 \tag{5.69}$$

The variable-head characteristics are shown in Table 5.12.

Table 5.12 Reservoir data for Case Study 1

Plant	Volume of water (V_j) *(Mft^3)*	Surface area (S_j) *(Mft^2)*	Initial height (h_{j0}) *(ft)*
1	2850	1000	300
2	2450	400	250

The constant of proportionality, K for the Glimn-Kirchmayer model is 1.0. The loss coefficients are given by the following B-matrix:

$$\mathbf{B} = 10^{-4}\begin{bmatrix} 1.40 & 0.10 & 0.15 & 0.15 \\ 0.10 & 0.60 & 0.10 & 0.13 \\ 0.15 & 0.10 & 0.68 & 0.65 \\ 0.15 & 0.13 & 0.65 & 0.70 \end{bmatrix} \tag{5.70}$$

The scheduling period is 1 day divided into 24 intervals. The load demand for each time interval over the scheduling period is given in Table 5.13.

Table 5.13 2 thermal and 2 hydro plants (load demand)

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	800	7	800	13	1300	19	1430
2	700	8	1000	14	1350	20	1350
3	600	9	1330	15	1350	21	1270
4	600	10	1350	16	1370	22	1150
5	600	11	1450	17	1450	23	1000
6	650	12	1500	18	1570	24	900

The MBFA is implemented to find the optimal generation schedule for this test system. The resultant power generation schedule for each of the four plants during each time interval is shown in Table 5.14. The table also shows the transmission power losses computed for each interval as well as the variation of water head in each of the two reservoirs. The generation power schedule and the total load demand over the scheduling period are also illustrated in Figure 5.6 while Figure 5.7 shows the variations of water head.

Table 5.14 2 thermal and 2 hydro plants (power and head variations)

Hour	Thermal Generation (MW)		Hydro Generation (MW)		P_L (MW)	Net head (*ft*)	
	Plant 1	Plant 2	Plant 1	Plant 2		Reservoir 1	Reservoir 2
1	148.3546	355.9633	279.9606	38.0552	22.3338	300.0000	250.0000
2	138.0000	289.8285	262.7690	25.6489	16.2464	299.9122	249.9897
3	120.5686	239.4195	243.5698	8.4296	11.9874	299.8649	249.9001
4	120.5689	239.6589	243.6690	8.0998	11.9966	299.7155	249.8547
5	121.5689	238.8846	243.5240	7.9987	11.9762	299.6649	249.8122
6	128.2421	266.1986	253.0040	16.5683	14.0130	299.5749	249.8001
7	151.9147	355.7013	278.3450	35.7443	21.7053	299.4875	249.7899
8	188.0446	455.7917	318.4062	71.9003	34.1429	299.4124	249.7786
9	242.3603	632.4225	386.2540	130.2142	61.2511	299.3546	249.6547
10	243.2540	644.2513	390.2335	135.4017	63.1405	299.3025	249.2356
11	256.9975	701.1861	410.9667	153.9907	73.1409	299.1453	249.0913
12	269.6401	723.1259	422.1050	163.5936	78.4646	299.0012	248.7955
13	237.4763	611.9343	380.8687	128.1829	58.4621	298.8848	248.3215
14	244.7819	640.1694	390.3917	137.9363	63.2792	298.7846	248.0113
15	244.7908	639.6128	390.4447	138.2557	63.1040	298.2155	247.8746
16	247.9560	651.2421	394.2402	142.2351	65.6734	298.1215	247.5486
17	261.7811	693.0391	410.6297	157.6633	73.1131	298.1015	246.9146
18	284.3111	754.3922	436.1635	181.2831	86.1499	298.0025	246.4999
19	255.8406	684.7927	405.1103	155.3212	71.0648	297.8547	246.0126
20	243.8624	636.7368	389.6489	142.8824	63.1306	297.7654	245.7655
21	231.8111	592.7259	373.4363	127.7302	55.7036	297.5848	245.0266
22	209.1116	532.1245	348.1811	106.1380	45.5552	297.4569	244.6326
23	183.8421	452.3462	318.1907	79.7213	34.1003	297.3486	244.4659
24	164.4493	402.7413	298.2103	62.1615	27.5624	297.2501	244.1549

The total operating cost is $ 67847.86 which is shown in Table 5.15 along with the mean and worse values obtained for the total cost. The table shows also the average processing time.

Table 5.15 2 thermal and 2 hydro plants (cost and time)

Cost ($)			Average time (sec)
Min	Max	Average	
67847.86	67852.46	67851.47	28.8569745

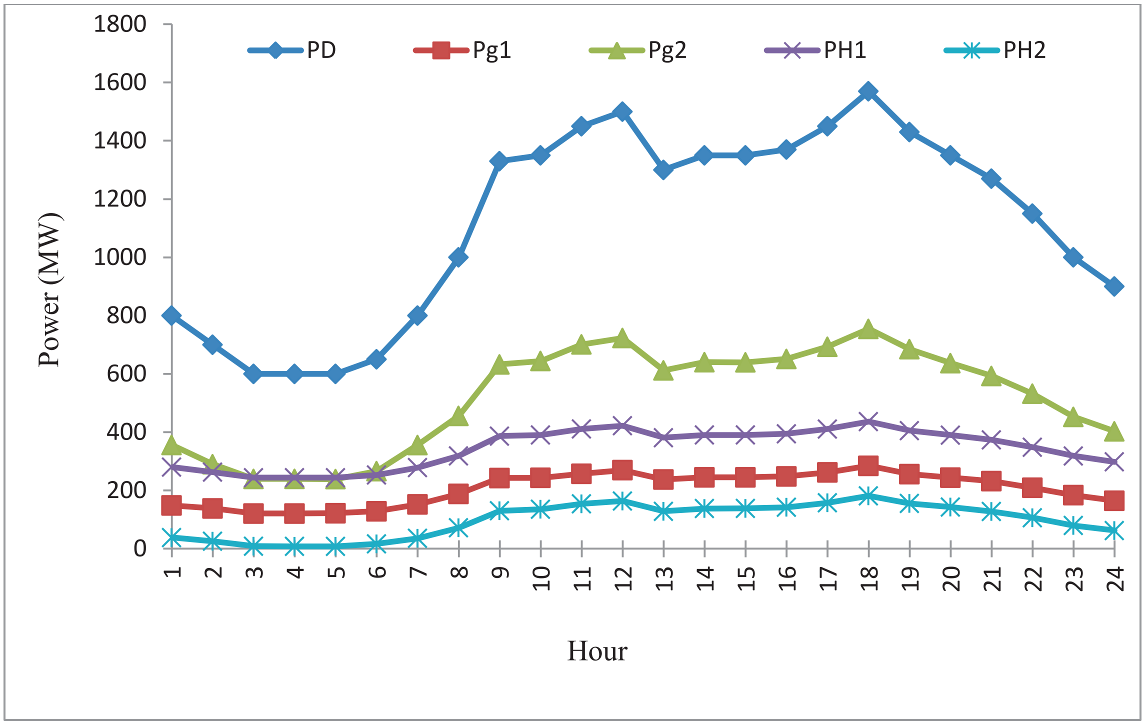

Figure 5.6 Load curve and optimal solution for Case Study 1

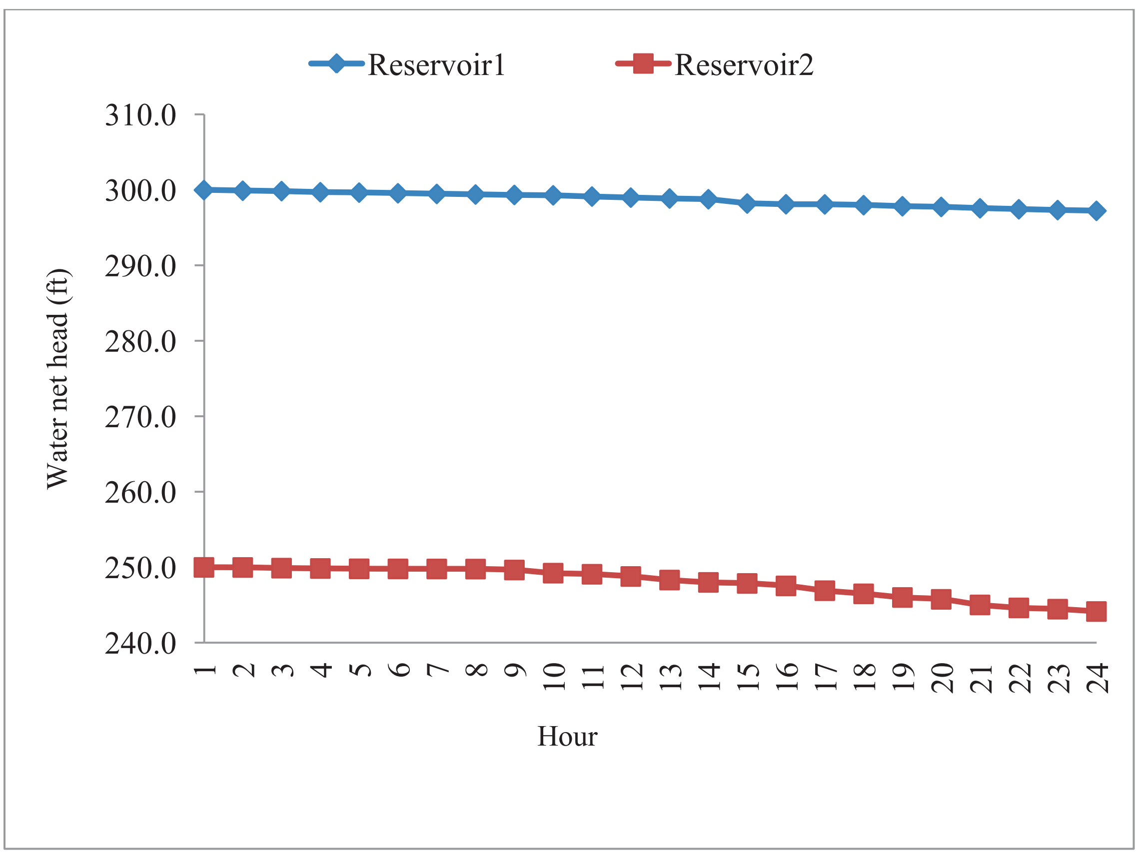

Figure 5.7 Water head variations for Case Study 1

5.3.8 Case Study 2: Five Thermal and Four Hydro Plants

In this case study [269], a system of five thermal generating plants and four hydro plants supplies power to a load over a transmission network. The characteristics of the thermal plants are given by the following fuel cost functions:

$$F_1(P_{g1_k}) = 0.003P_{g1_k}^2 + 2.7P_{g1_k} + 150 \quad \$/h \tag{5.71}$$

$$F_2(P_{g2_k}) = 0.003P_{g2_k}^2 + 2.8P_{g2_k} + 150 \quad \$/h \tag{5.72}$$

$$F_3(P_{g3_k}) = 0.003P_{g3_k}^2 + 3.0P_{g3_k} + 150 \quad \$/h \tag{5.73}$$

$$F_4(P_{g4_k}) = 0.003P_{g4_k}^2 + 3.1P_{g4_k} + 150 \quad \$/h \tag{5.74}$$

$$F_5(P_{g5_k}) = 0.003P_{g5_k}^2 + 3.2P_{g5_k} + 150 \quad \$/h \tag{5.75}$$

The B-coefficients are given as follows:

$$B_{m0} = 0.0 \quad , m = 0,1,2,...,9 \tag{5.76}$$

$$B_{mn} = 0.0 \quad , m \neq n \quad m,n = 1,2,...,9 \tag{5.77}$$

$$B_{mm} = 0.143\times10^{-3} \quad , m = 1,2,...,9 \tag{5.78}$$

The Hamilton-Lamont models of the hydro plants are defined by Equation (5.6) with the hydro model coefficients given as follows:

$$a_0 = 29.46925\times10^{-1}, a_1 = -74.96985\times10^{-4}, a_2 = 63.54239\times10^{-7}$$

$$b_0 = 14.42652\times10^{-2}, b_1 = 71.43352\times10^{-4}, b_2 = 2.11535\times10^{-8}$$

The surface area of each reservoir is $6.9695\times10^7 \ ft^2$ and the volume of water available is $1.1678\times10^9 \ ft^3$. The effective net head and the inflow of water into each of the four reservoirs are given in Table 5.16. The load demand for each time interval of the scheduling period is given in Table 5.17.

Table 5.16 Reservoir data for Case Study 2

Plant	Net initial head, (h_{j0}) (Mft)	Inflow of water (I_j) (ft^3/h)
1	590	1.80×10^4
2	591	2.16×10^4
3	592	2.52×10^4
4	593	2.88×10^4

Table 5.17 5 thermal and 4 hydro plants (load demand)

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	5448	7	6088	13	5400	19	3584
2	5776	8	5856	14	5828	20	3544
3	5664	9	5480	15	3928	21	3528
4	5624	10	5464	16	3840	22	3552
5	5928	11	5728	17	3784	23	3688
6	6064	12	5536	18	3608	24	3840

The optimal power generation schedule is obtained for this hydro-thermal system using the MBFA. This schedule along with the hourly transmission power losses is presented in Table 5.18 and depicted in Figure 5.8.

Table 5.18 5 thermal and 4 hydro plants (power schedule and losses)

Hour	Thermal Generation (MW)					Hydro Generation (MW)				P_L
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 5	Plant 1	Plant 2	Plant 3	Plant 4	(MW)
1	852.300	859.366	827.387	805.884	794.579	483.279	483.888	482.889	482.476	624.048
2	898.323	887.701	866.012	855.244	844.707	531.277	531.828	532.563	532.173	703.828
3	878.685	867.686	845.840	834.774	823.776	520.760	521.108	521.687	522.294	672.609
4	871.729	860.669	838.609	827.730	816.299	517.228	517.119	518.109	518.218	661.708
5	925.785	915.207	893.117	882.239	871.619	546.001	546.160	547.438	547.842	747.409
6	949.673	939.278	918.106	907.182	896.221	559.522	560.182	560.322	561.320	787.808
7	954.183	943.825	922.618	911.369	901.124	561.666	562.643	562.730	563.043	795.198
8	912.730	901.687	880.178	869.336	858.139	539.436	539.685	540.438	540.775	726.402
9	846.248	835.370	813.239	801.575	790.008	503.229	504.240	504.238	505.183	623.327
10	843.337	832.789	809.628	798.728	787.940	501.618	502.673	502.627	503.830	619.168
11	889.732	878.284	857.101	846.222	834.321	527.224	527.453	528.861	528.824	690.023
12	855.664	845.282	822.108	811.148	800.244	509.189	509.330	510.177	510.738	637.880
13	832.183	821.830	798.127	787.327	775.829	496.163	496.164	497.360	497.633	602.616
14	907.113	896.274	874.021	863.608	852.731	537.163	537.524	538.160	539.424	718.020
15	585.683	574.218	549.228	537.101	524.321	362.221	363.123	363.345	364.121	295.361
16	566.618	559.826	535.994	523.628	512.262	355.563	355.003	355.749	356.248	280.891
17	563.118	550.107	526.228	513.107	501.587	349.669	350.275	350.774	351.247	272.112
18	534.668	522.119	497.618	484.667	472.616	334.239	335.279	335.375	336.557	245.137
19	530.923	518.607	493.700	481.326	468.823	332.563	332.742	333.221	333.733	241.637
20	524.607	512.207	487.414	474.618	462.224	329.125	329.213	330.200	330.170	235.779
21	522.116	510.162	484.640	472.183	459.130	327.332	328.226	328.260	329.421	233.470
22	526.189	513.774	488.116	476.682	463.168	329.178	330.214	330.628	331.023	236.970
23	547.829	535.188	510.177	497.775	485.062	341.127	342.236	342.567	343.229	257.191
24	571.568	559.468	534.677	522.338	509.786	354.625	355.578	356.170	356.729	280.938

The hourly variation of the net head over the scheduling period is tabulated in Table 5.19 and illustrated in Figure 5.9. The minimum total fuel cost for this system was computed to be $ 467,101 as shown in Table 5.20 which also shows the maximum and average computed cost and the processing time for convergence.

Table 5.19 5 thermal and 4 hydro plants (Net head variations)

Hour	Net head (*ft*)			
	Reservoir1	Reservoir2	Reservoir3	Reservoir4
1	589.9767	590.9852	591.9774	592.9859
2	589.1930	590.2015	591.2101	592.2022
3	588.3251	589.3336	590.3422	591.3507
4	587.4886	588.4971	589.5007	590.5092
5	586.6685	587.6770	588.6806	589.6891
6	585.7478	586.7727	587.7812	588.7898
7	584.8120	585.8156	586.8405	587.8490
8	583.8549	584.8749	585.8834	586.9083
9	582.9556	583.9805	585.0055	586.0304
10	582.1455	583.1704	584.2118	585.2367
11	581.3568	582.3817	583.4067	584.4316
12	580.4889	581.5138	582.5552	583.5801
13	579.6738	580.6987	581.7401	582.8142
14	578.8687	579.9100	580.9514	581.9927
15	577.9858	579.0107	580.0520	581.0934
16	577.4797	578.5210	579.5624	580.6037
17	577.0114	578.0528	579.0941	580.1355
18	576.5318	577.5895	578.6309	579.6722
19	576.0949	577.1363	578.1940	579.2354
20	575.6467	576.7044	577.7622	578.8035
21	575.2148	576.2726	577.3303	578.3881
22	574.7830	575.8407	576.8985	577.9562
23	574.3511	575.4089	576.4666	577.5244
24	573.8929	574.9506	576.0248	577.0825

Table 5.20 5 thermal and 4 hydro plants (total cost and time)

Cost ($)			Average time (sec)
Min	Max	Average	
467,101.02	467,175.75	467,113.52	69.058282

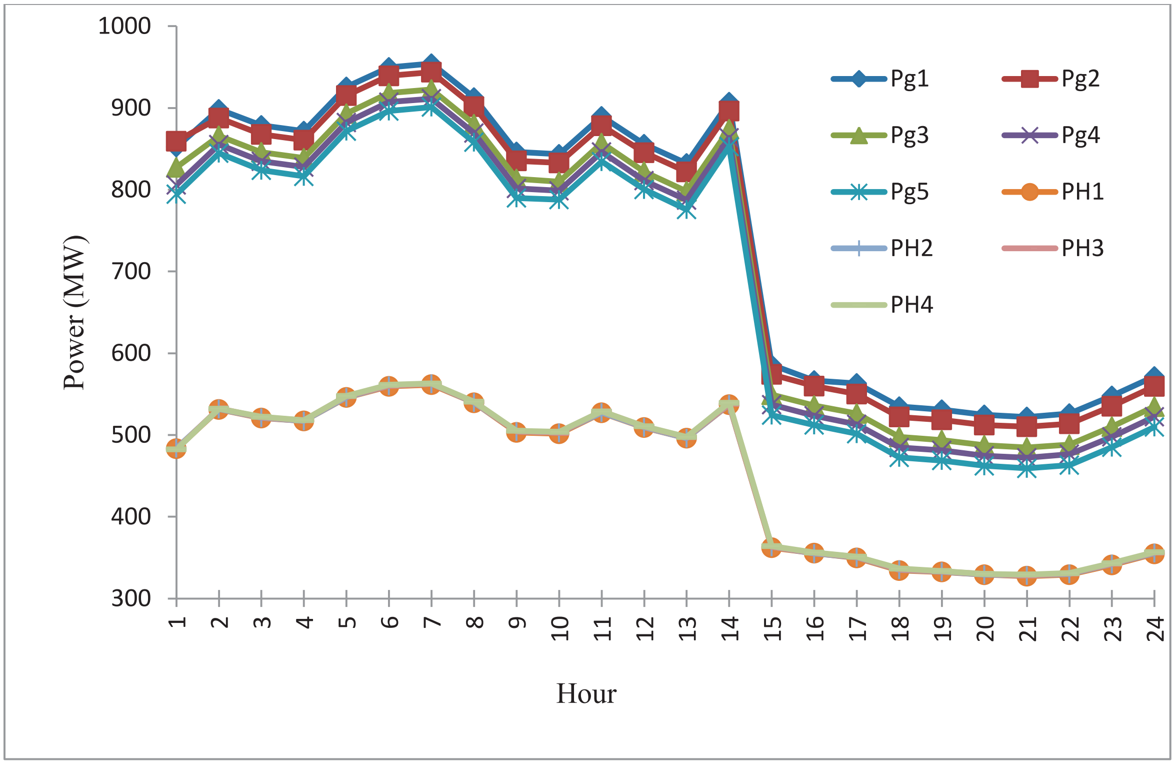

Figure 5.8 Hourly power schedule for Case Study 2

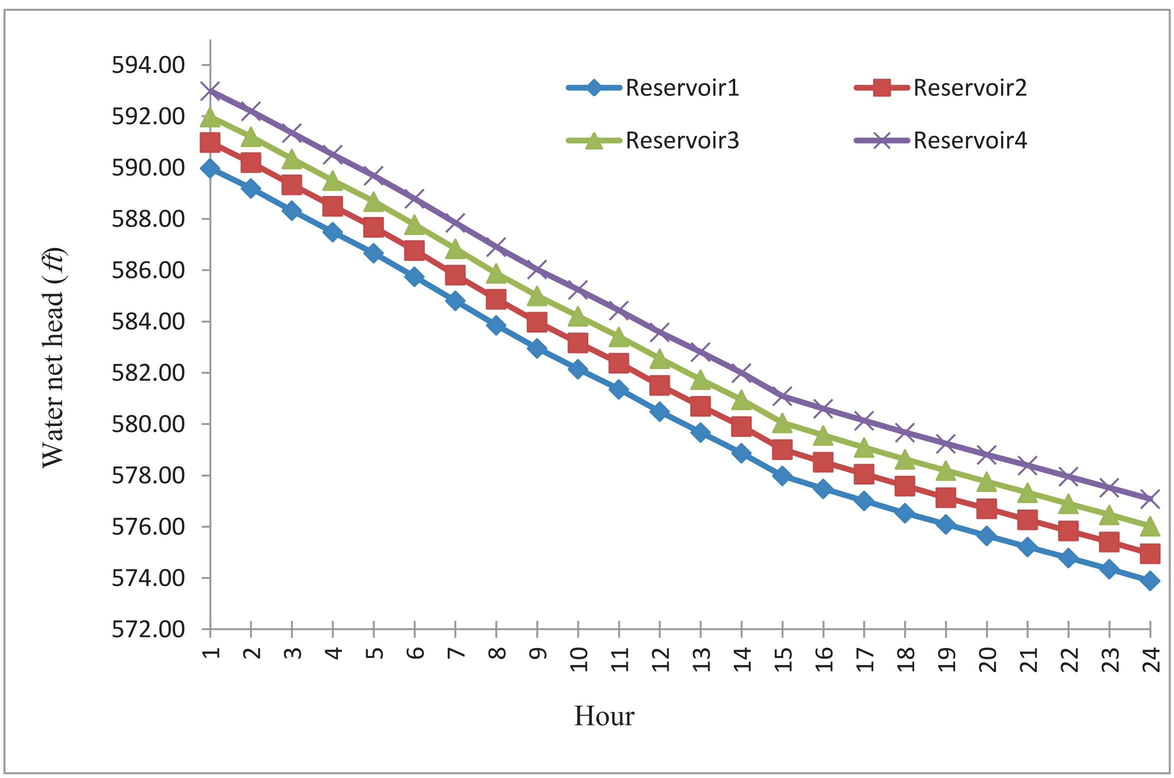

Figure 5.9 Hourly variation of net head for Case Study 2

5.4 MULTI-CHAIN HYDRO-THERMAL GENERATION SCHEDULING

In this section, the hydraulic coupling between hydro plants is considered. As mentioned in 5.1.2, hydro plants can be located on the same stream or on different streams. Figure 5.10 shows a typical combination of hydro plants on the same stream and different streams. In this situation, reservoirs could or could not be dependent of each other and several plants may or may not be located in series on the same river. Water released from the upstream reservoirs in addition to the stream water put together the reservoir inflow. Time delay could also be an important factor which affects the water flow from upstream to downstream reservoir. Due to many reasons, some water can be lost during its travel to the reservoir.

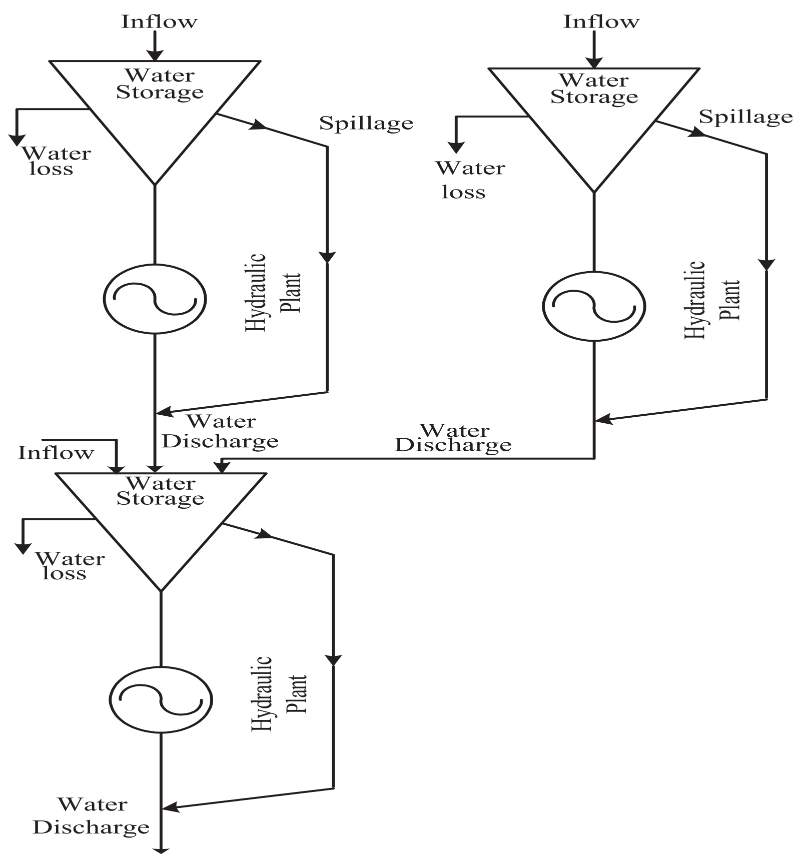

Figure 5.10 Multi-chain hydro plants on the same stream and on different streams

5.4.1 Thermal Model and Objective Function

The hydro-thermal generation system considered for this scheduling problem consists of N_g thermal generating plants and M_H hydro plants. The scheduling period T

is divided into N_k time sub-intervals with n_k hours each. The objective is to minimize the operating cost and use up the entire available amount of water during the scheduling period. The optimization problem is expressed in discrete form as follows:

$$Minimize \qquad F_T = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k \,(a_i P_{gi_k}^2 + b_i P_{gi_k} + c_i) \tag{5.79}$$

where P_{gi_k} : power generation of thermal unit i at time interval k

N_k : number scheduling time intervals

n_k : number of hours in scheduling time interval k

a_i, b_i, c_i : cost coefficients of the i^{th} thermal generating unit.

5.4.2 Hydraulic Continuity Equation

Taking into consideration the influence of water flow from upstream reservoirs into downstream ones and the associated time delay in addition to water losses, the water inflow into a reservoir can be modeled as follows:

$$I_{j_k} = J_{j_k} + \sum_{u=1}^{M_u} [Q_{u_{k-\tau_u}} + S_{u_{k-\tau_u}}] - L_{j_k} \tag{5.80}$$

where J_{j_k} : inflow to the reservoir j during the time interval k

M_u : number of immediate upstream reservoirs

$Q_{u_{k-\tau_u}}$: discharge from the u^{th} immediate upstream reservoir during the time interval k after a time delay τ_u

$S_{u_{k-\tau_u}}$: spillage from the u^{th} immediate upstream reservoir during the time interval k after a time delay τ_u

L_{j_k} : water losses from the inflow to reservoir j during the interval k

On the other hand, water could be lost due to various reasons such as irrigation schemes and evaporation. In addition to water losses, water overflow and spillage are also outflows from the reservoir. These reservoir outflows can be modeled as follows:

$$O_{j_k} = Q_{j_k} + S_{j_k} + R_{j_k} \tag{5.81}$$

where Q_{j_k} : water discharge from the reservoir j during the time interval k

S_{j_k} : water spillage from the reservoir j during the time interval k

R_{j_k} : water losses from the reservoir j during the time interval k

The water storage in the reservoir j at the beginning of the time interval k is modeled as the following:

$$X_{j_{k+1}} = X_{j_k} + I_{j_k} - O_{j_k} \tag{5.82}$$

where X_{j_k} is the water storage in the reservoir j at the end of time interval k. Equation (5.82) can be rewritten as follows after including Equations (5.80) and(5.81):

$$X_{j_{k+1}} = X_{j_k} + J_{j_k} - Q_{j_k} - S_{j_k} + \sum_{u=1}^{M_u}[Q_{u_{k-\tau_u}} + S_{u_{k-\tau_u}}] - (L_{j_k} + R_{j_k}) \tag{5.83}$$

The total volume of water available at the end of the scheduling period can be computed using Equation (5.83) so that the following equation is satisfied:

$$X_{j_{k+1}}|_{k=N_k} = X_{j_k}|_{k=1} + \sum_{k=1}^{N_k}[J_{j_k} - Q_{j_k} - S_{j_k} + \sum_{u=1}^{M_u}[Q_{u_{k-\tau_u}} + S_{u_{k-\tau_u}}] - (L_{j_k} + R_{j_k})] \tag{5.84}$$

5.4.3 Hydro Model

Modeling the generated hydro-electric power depends on the discharge rate and the head of water in addition to the efficiency of the hydro plant itself. The active power generation produced by the j^{th} hydro plant during the time interval k is given by [3]:

$$P_{Hj_k} = q_{j_k} h_{j_k} / G_j \tag{5.85}$$

where G_j is the efficiency constant for the hydro plant j. For reservoirs with large variations in their head water, the head cannot be considered constant during the sub-interval. Accordingly, Equation (5.85) is reformulated so that the average hydro power during a sub-interval depends on the average head which in turn depends on the capacity of the reservoir. The average hydro-electric power generated during the time interval k can be computed as follows [278, 279]:

$$P_{Hj_k} = 9.81 \times 10^{-3} \overline{h}_{j_k} (Q_{j_k} - \mu_j) \tag{5.86}$$

where $Q_j - \mu_j$: effective discharge rate

$\bar{h}_{j_k}$: average water head in the reservoir j during time interval k

The average water head $\bar{h}_{j_k}$ is defined by:

$$\bar{h}_{j_k} = h_{j_0} + \frac{\Delta T\,(X_{j_{k+1}} + X_{j_k})}{2A} \tag{5.87}$$

where h_{j_0} : basic initial water head of the reservoir j

ΔT : time length

X_{j_k} : water storage in the reservoir j at the end of time interval k

A : area of the reservoir j at the given storage

Equation (5.86) can be rewritten as follows:

$$P_{Hj_k} = h_j [1 + \frac{1}{2} g_j (X_{j_{k+1}} + X_{j_k})](Q_{j_k} - \mu_j) \tag{5.88}$$

where $g_j = \Delta T / A h_{j_0}$ which is tabulated for various storage values and $h_j = 9.81 \times 10H^{-3} h_{j_0}$.

5.4.4 Constraints

The following equality and inequality constraints, that include thermal and hydro operational constraints, must be satisfied:

- Load balance equation:

$$\sum_{i=1}^{N_g} P_{gi_k} + \sum_{j=1}^{M_H} P_{Hj_k} - P_{D_k} - P_{L_k} = 0 \tag{5.89}$$

where P_{D_k} : total load demand during the time interval k

P_{L_k} : total transmission power losses during the time interval k

The transmission power losses are given by the following redefined loss formula:

$$P_{L_k} = \sum_{i=1}^{N_g + M_H} \sum_{j=1}^{N_g + M_H} P_{i_k} B_{ij} P_{j_k} + \sum_{i=1}^{N_g} B_{i0} P_{i_k} + B_{00} \tag{5.90}$$

- Generation boundary condition:

$$P_{gi_k}^{\min} \le P_{gi_k} \le P_{gi_k}^{\max} \tag{5.91}$$

$$P_{Hj_k}^{\min} \le P_{Hj_k} \le P_{Hj_k}^{\max} \tag{5.92}$$

- Water discharge limits:

$$Q_{j_k}^{\min} \le Q_{j_k} \le Q_{j_k}^{\max} \tag{5.93}$$

- Reservoir forebay limits:

$$X_{j_k}^{\min} \le X_{j_k} \le X_{j_k}^{\max} \tag{5.94}$$

5.4.5 Case Study 1: One Thermal and Four Hydro Plants

The hydro-thermal generation system of this case study consists of a multi-chain cascade of four hydro plants and an equivalent thermal unit with the following characteristics [81]:

$$F_1(P_{g1_k}) = 0.002P_{g1_k}^2 + 19.2P_{g1_k} + 500 \quad \$/h \tag{5.95}$$

The scheduling period is 24 hours of 1-hour intervals. The load demand over the 24 hours of the scheduling horizon is variable as shown in Table 5.21.

Table 5.21 Multi-chain 1 thermal and 4 hydro plants (load demand)

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	1370	7	1650	13	2230	19	2240
2	1390	8	2000	14	2200	20	2280
3	1360	9	2240	15	2130	21	2240
4	1290	10	2320	16	2070	22	2120
5	1290	11	2230	17	2130	23	1850
6	1410	12	2310	18	2140	24	1590

The characteristics of the hydraulic sub-system are as follows:

- A multi-chain cascade flow network, with all the plants on one stream
- River transport delay between successive reservoirs
- Variable-head hydro plants
- Variable natural inflow into each reservoir

The output hydro power is expressed as a function of the water discharge rate and the reservoir storage [81]:

$$P_{Hj_k} = C_{j_1}X_{j_k}^2 + C_{j_2}Q_{j_k}^2 + C_{j_3}X_{j_k}Q_{j_k} + C_{j_4}X_{j_k} + C_{j_5}Q_{j_k} + C_{j_6} \tag{5.96}$$

where $C_{j_1}, C_{j_2}, \ldots, C_{j_6}$ the hydro power generation coefficients of the hydro plant j that are given in Table 5.23.

Table 5.22 Multi-chain Water Time Delays

Plant	1	2	3	4
C_1	-0.0042	-0.0040	-0.0016	-0.0030
C_2	-0.4200	-0.3000	-0.3000	-0.3100
C_3	0.0300	0.0150	0.0140	0.0270
C_4	0.9000	1.1400	0.5500	1.4400
C_5	10.0000	9.5000	5.5000	14.0000
C_6	-50.0000	-70.0000	-40.0000	-90.0000

The configuration of the hydraulic sub-system is shown in Figure 5.11 and the water time delays are shown in Table 5.23.

Table 5.23 Multi-chain Water Time Delays

Plant	1	2	3	4
M_u	0	0	2	1
τ_u	2	3	4	0
M_u: Number of up-stream plants				
τ_u: Time delay to immediate down-stream plant				

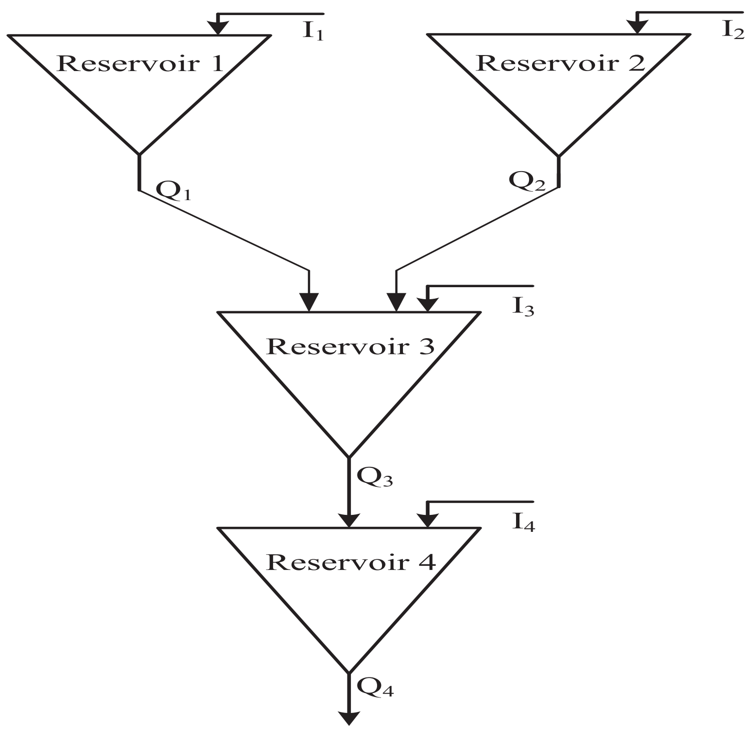

Figure 5.11 Multi-chain hydro sub-system configuration

The reservoir inflows are shown in Table 5.24 while Table 5.25 shows the reservoir storage limits, plant discharge and generation limits as well as reservoir end conditions.

Table 5.24 Multi-chain reservoir inflows ($\times 10^4$ m^3)

Hour	Reservoir				Hour	Reservoir				Hour	Reservoir			
	1	2	3	4		1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	9	10	8	1	0	17	9	7	2	0
2	9	8	8.2	2.4	10	11	9	1	0	18	8	6	2	0
3	8	9	4	1.6	11	12	9	1	0	19	7	7	1	0
4	7	9	2	0	12	10	8	2	0	20	6	8	1	0
5	6	8	3	0	13	11	8	4	0	21	7	9	2	0
6	7	7	4	0	14	12	9	3	0	22	8	9	2	0
7	8	6	3	0	15	11	9	3	0	23	9	8	1	0
8	9	7	2	0	16	10	8	2	0	24	10	8	0	0

Table 5.25 Discharge and generation limits and end conditions ($\times 10^4$ m^3)

Plant	V^{min}	V^{max}	V_{ini}	V_{end}	Q^{min}	Q^{max}	P_h^{min}	P_h^{max}
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	13	25	0	500

The resultant power generation schedule is illustrated by Table 5.26 and Figure 5.12. Figure 5.13 and Table 5.27 show the hourly plant discharge while Figure 5.14 shows the hourly reservoirs volume storage.

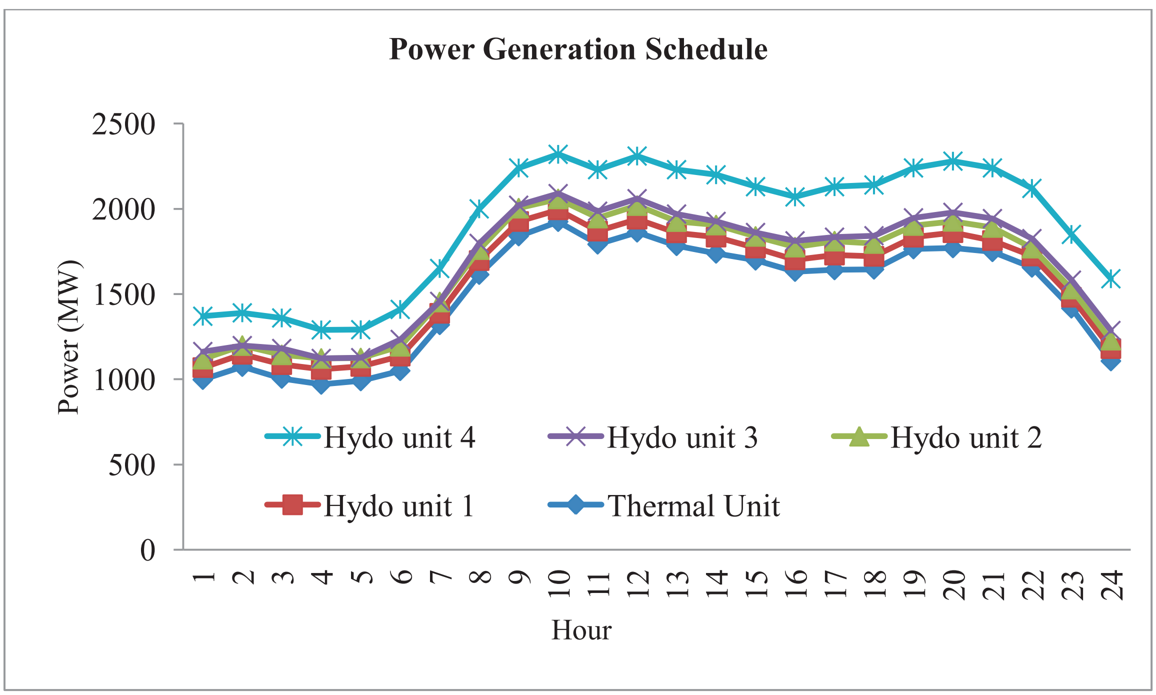

Figure 5.12 Hourly generation schedule

Table 5.26 Hourly generation schedule

Hour	Thermal Gen. (MW)	Hydro Generation (MW)			
		Plant1	Plant2	Plant3	Plant4
1	998.1245	70.6318	49.4315	44.6451	207.1672
2	1074.3854	72.3041	51.1175	0.0000	192.1929
3	1004.8847	81.3434	57.3801	37.0635	179.3282
4	969.8519	87.9233	64.5530	0.0000	167.6719
5	991.2731	85.1440	49.4039	0.0000	164.1790
6	1050.2135	85.9362	57.4993	40.1884	176.1625
7	1319.7871	67.4328	66.2426	3.7119	192.8256
8	1614.4211	82.2345	64.3780	36.3289	202.6375
9	1840.4474	85.3862	78.2000	17.2705	218.6958
10	1924.9482	69.6812	63.8037	30.9123	230.6545
11	1792.2396	77.2081	76.4123	40.3747	243.7654
12	1862.8032	76.8696	79.5482	40.3443	250.4347
13	1783.3329	76.0455	66.0873	44.1866	260.3477
14	1738.9041	95.0695	70.9690	21.3171	273.7403
15	1698.1514	72.0967	68.2102	22.8079	268.7338
16	1631.9894	68.9814	74.4922	36.9912	257.5458
17	1641.7019	87.1597	81.6873	23.2795	296.1717
18	1645.1942	76.2198	75.4043	45.4671	297.7146
19	1764.3167	69.4578	68.6507	45.0866	292.4882
20	1770.7074	89.5220	66.6308	52.4570	300.6828
21	1747.9577	66.2677	76.5256	52.2151	297.0339
22	1656.6815	66.5803	46.2813	55.8176	294.6394
23	1416.8735	64.3999	48.1640	52.1633	268.3995
24	1107.3584	72.4779	49.7578	56.7251	303.6807

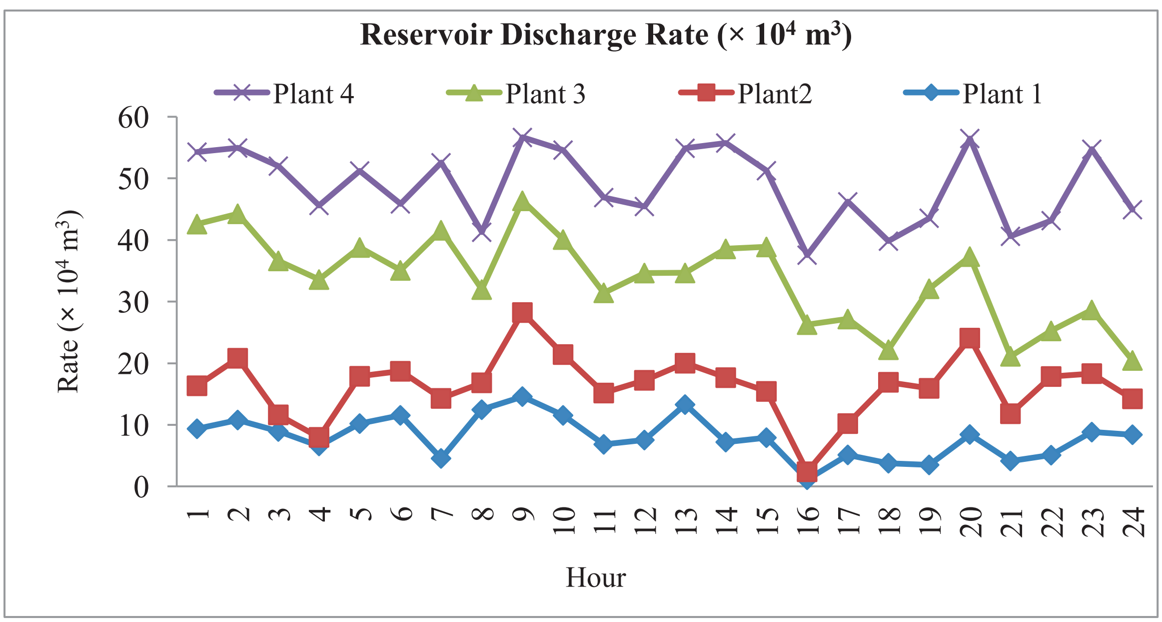

Figure 5.13 Hourly water discharge

Table 5.27 Hourly reservoir discharge

Hour	Reservoirs Discharge ($\times 10^4$ m^3)			
	Plant1	Plant2	Plant3	Plant4
1	9.3757	6.9780	26.2410	11.6832
2	10.7982	10.0199	23.4504	10.6683
3	8.9383	2.6954	24.9851	15.3918
4	6.5943	1.3873	25.6105	12.0296
5	10.2182	7.6720	20.9088	12.4197
6	11.5530	7.1555	16.3718	10.7886
7	4.5659	9.7415	27.2808	10.9559
8	12.4711	4.3637	15.1315	9.3013
9	14.5999	13.6377	18.1379	10.2765
10	11.5454	9.8751	18.6653	14.5182
11	6.8473	8.3285	16.2645	15.4572
12	7.5493	9.6935	17.4064	10.7986
13	13.3025	6.7184	14.6434	20.2343
14	7.2175	10.4517	20.8994	17.1791
15	7.9352	7.5056	23.4430	12.3776
16	1.1104	1.2911	23.8760	11.2793
17	5.1389	5.0775	16.9724	19.0173
18	3.7883	13.1326	5.2811	17.6216
19	3.5124	12.4264	16.1591	11.4474
20	8.4484	15.6424	13.2269	19.1721
21	4.1504	7.6677	9.3229	19.4667
22	5.0950	12.7606	7.4049	17.8900
23	8.8357	9.4926	10.3372	26.0766
24	8.4111	5.8237	6.2295	24.4613

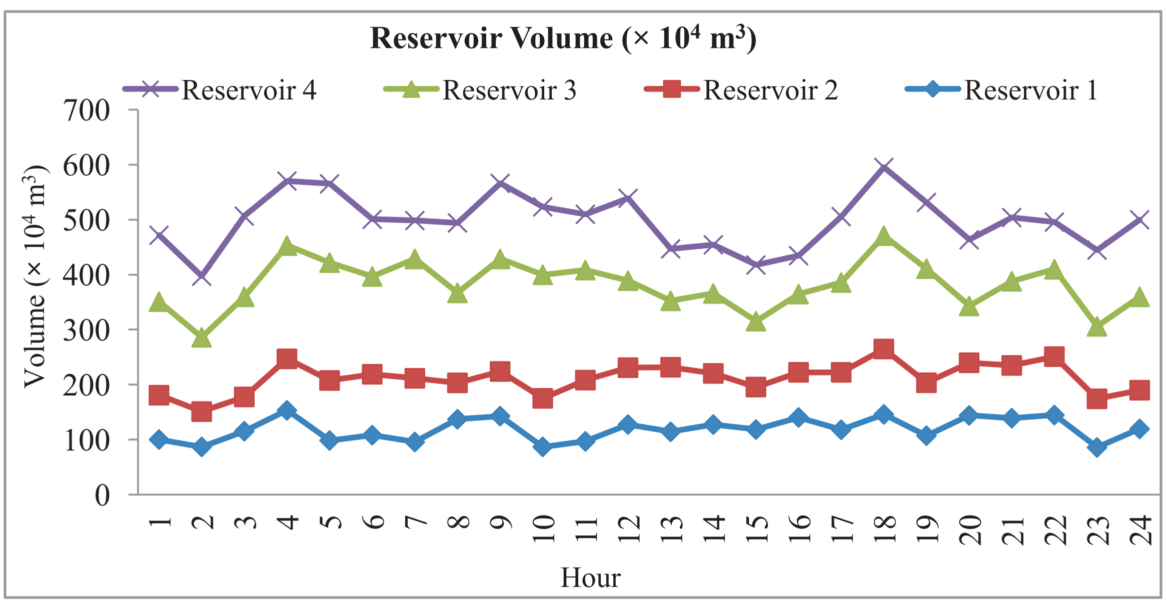

Figure 5.14 Hourly water volume

The cost obtained by the proposed algorithm is compared to those obtained by the Genetic Algorithm (GA) applied in [81], Classical, Fast and Improved Fast Evolutionary Programming (CEP, FEP and IFEP) techniques proposed in [107] and the Particle Swarm Optimization (PSO) of [98]. Table 5.28 shows the comparison of these methods.

Table 5.28 Comparison of the cost function

	Total Cost ($)			Average time
Method	Min	Max	Average	(sec)
GA [81]	942600.00	951087.00	946609.10	1920.00
CEP [107]	930166.25	930927.01	930373.23	2292.10
FEP [107]	930267.92	931396.81	930897.44	1911.20
IFEP [107]	930129.82	930881.92	930290.13	1033.20
PSO [98]	925383.80	927240.10	926352.80	82.90
MBFA	925060.13	927329.07	926235.24	74.80

5.4.6 Case Study 2: One Thermal and Four Hydro Plants, Valve-Point Effects Considered

In this case the same system of Case Study1 is employed considering the valve-point effects [107]. Applying Equation (4.19), the fuel cost function of Equation (5.95) is modified as follows:

$$\begin{aligned} F_1(P_{g1_k}) &= 0.002P_{g1_k}^2 + 19.2P_{g1_k} + 500 \\ &+ \left|700\sin\left(0.085(P_{g1_k}^{\min} - P_{g1_k})\right)\right| \quad \$/h \end{aligned} \tag{5.97}$$

The proposed MBFA is applied to this system and the resultant power schedule is given in Table 5.29 and illustrated in Figure 5.15. Water discharge rates over the scheduling period are shown in Table 5.30 and Figure 5.16 while the corresponding water volume is shown in Figure 5.17.

The results are compared to those obtained by Classical, Fast and Improved Fast Evolutionary Programming (CEP, FEP and IFEP) techniques proposed in [107]. This comparison is reported in Table 5.31.

Table 5.29 Hourly generation schedule

Hour	Thermal Gen. (MW)	Hydro Generation (MW)			
		Plant1	Plant2	Plant3	Plant4
1	1016.8556	86.2318	63.3437	0.0000	203.5689
2	1054.1503	92.8598	55.2978	0.0000	187.6921
3	1054.0789	81.3289	51.3250	0.0000	173.2672
4	980.2513	86.6972	66.6742	0.0000	156.3772
5	943.7891	68.3645	59.1781	40.2948	178.3735
6	1091.4024	67.0325	53.1121	0.0000	198.4530
7	1276.3498	53.5479	70.5188	33.5457	216.0378
8	1609.0910	63.3493	53.5346	41.4126	232.6124
9	1830.0094	82.9849	52.8488	41.6789	232.4780
10	1867.6986	85.6139	75.9736	42.5727	248.1413
11	1793.2735	85.7686	54.5300	44.9789	251.4490
12	1904.7731	56.0224	55.0025	45.1003	249.1017
13	1794.2336	87.3779	57.3612	40.6587	250.3686
14	1793.7513	66.6937	58.8897	33.7885	246.8768
15	1682.6529	78.2849	71.8563	47.2375	249.9684
16	1646.1329	69.8793	62.4794	44.8345	246.6740
17	1645.4773	89.6965	84.8854	40.9452	268.9955
18	1645.8389	76.1341	82.2342	41.3621	294.4307
19	1793.6868	87.4519	56.4960	46.8941	255.4712
20	1792.8884	54.8774	85.7743	51.6855	294.7744
21	1756.8632	73.7543	84.4430	51.8328	273.1067
22	1608.5366	73.3026	77.0334	55.6752	305.4522
23	1349.9287	78.3664	73.1418	56.3548	292.2083
24	1128.5978	66.5365	45.1128	58.7315	291.0215

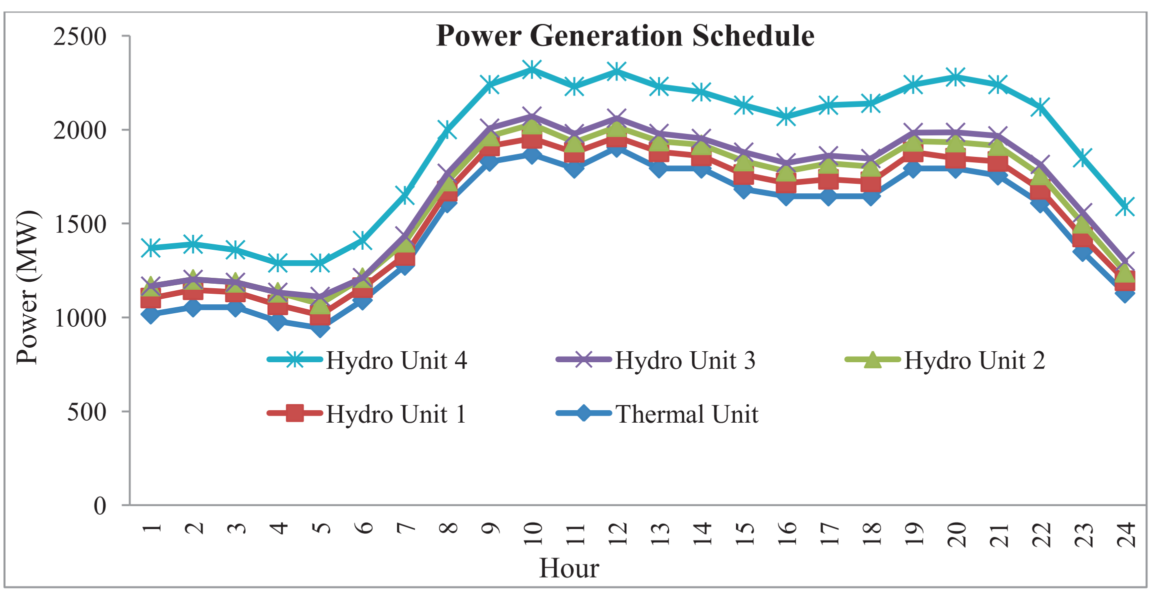

Figure 5.15 Hourly generation schedule

Table 5.30 Hourly reservoir discharge

Hour	Reservoirs Discharge (× 10^4 m^3)			
	Plant1	Plant2	Plant3	Plant4
1	9.9890	8.3123	29.5567	13.6248
2	11.2823	6.6087	29.6044	13.1602
3	8.6506	5.5684	29.1149	12.6019
4	10.3887	7.6187	29.3481	13.3356
5	7.1505	7.1548	12.7920	12.5452
6	7.3228	5.6867	29.2273	13.6494
7	5.0403	9.3703	16.3882	13.5331
8	7.2793	6.4725	12.4364	13.4143
9	9.1174	6.5150	11.7273	13.0949
10	9.9415	10.0151	12.2625	13.1285
11	9.7253	5.6837	11.7192	12.7448
12	5.1135	6.0713	13.4792	12.8619
13	9.7370	6.3442	16.8187	13.2548
14	6.5773	6.5105	18.6437	12.5715
15	7.6569	8.4631	14.0430	13.5939
16	6.2917	6.6623	14.9920	13.0639
17	9.8471	10.9018	16.7373	15.6732
18	8.0974	11.0470	16.5795	18.5049
19	9.0000	6.3832	14.8062	13.7657
20	4.7275	13.7813	13.1195	18.4163
21	7.4604	14.5468	9.8415	16.0119
22	7.6523	11.8695	12.4153	21.4178
23	8.1335	12.7386	10.4889	20.4729
24	6.3493	5.5502	14.1375	21.2377

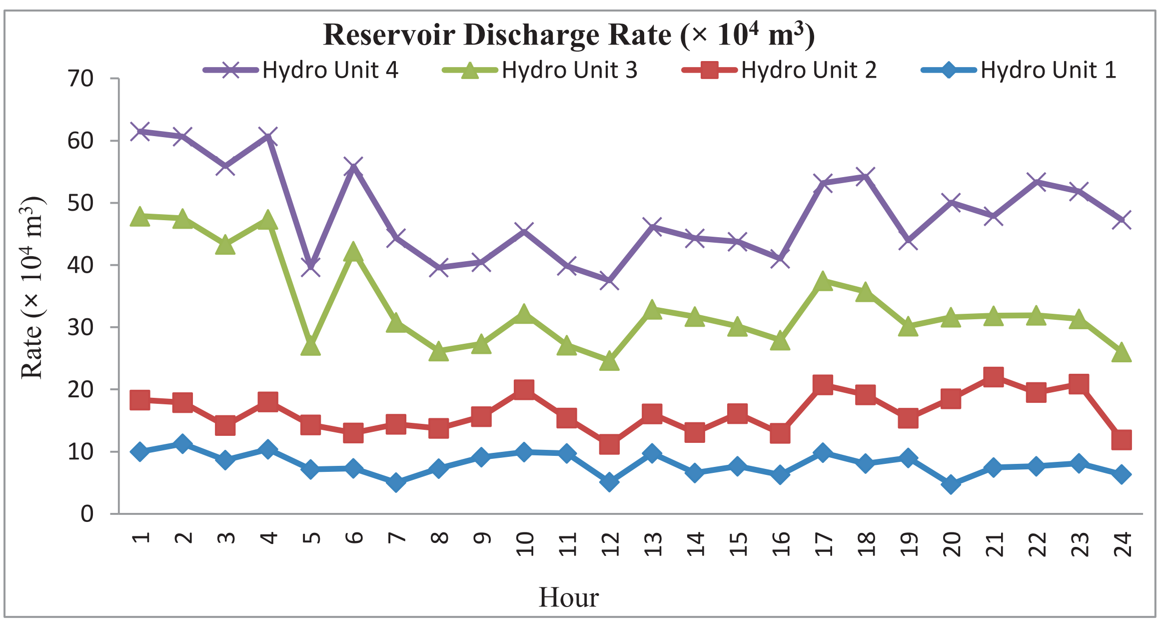

Figure 5.16 Hourly water discharge

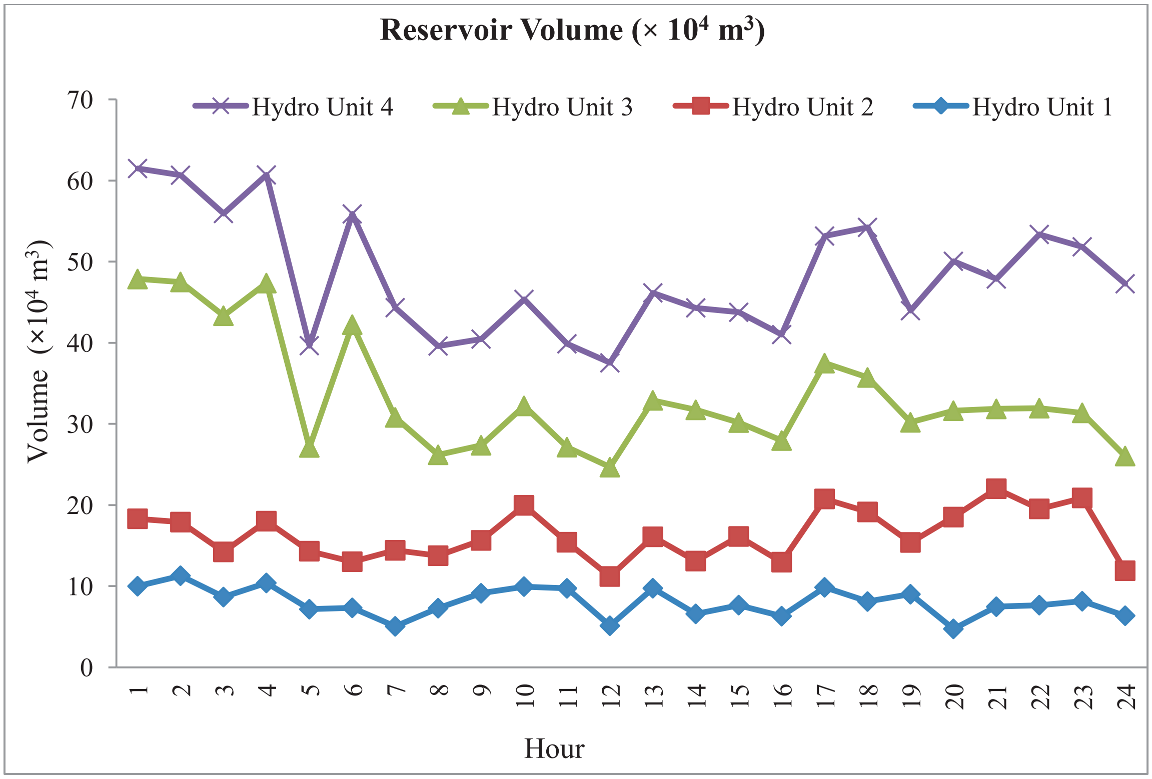

Figure 5.17 Hourly water volume

Table 5.31 Comparison of the cost function

Method	Total Cost ($) Min	Max	Average	Average time (sec)
CEP [107]	934713.18	946795.20	938801.47	2790.40
FEP [107]	935021.93	951524.37	942262.75	2289.20
IFEP [107]	933949.25	942593.02	938508.87	1450.90
MBFA	926340.15	926649.73	926488.85	98.27

5.4.7 Case Study 3: Three Thermal and Four Hydro Plants, Valve-Point Effects Considered

In this case, the system consists of the same four hydro plants of the system of Case Study1 in addition to three thermal generating units [129]. The characteristics of the hydraulic sub-system are as shown in Case Study1 while the thermal units' input-output characteristics are shown in Table 5.32 and the load demand is shown in Table 5.33.

Table 5.32 Coefficients and operating limits of thermal units

Unit	Coefficient and Operating Limits						
	a	*b*	*c*	*e*	*f*	Ps^{min}	Ps^{max}
1	100	2.45	0.0012	160	0.038	20	175
2	120	2.32	0.0010	180	0.037	40	300
3	150	2.10	0.0015	200	0.035	50	500

Table 5.33 Multi-chain 3 thermal and 4 hydro plants (load demand)

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	750	7	950	13	1110	19	1070
2	780	8	1010	14	1030	20	1050
3	700	9	1090	15	1010	21	910
4	650	10	1080	16	1060	22	860
5	670	11	1100	17	1050	23	850
6	800	12	1150	18	1120	24	800

The MBFA is applied to find the optimal generation scheduling for this system which is shown in Table 5.34 and Figure 5.18. Water discharge and volume are shown in Table 5.35, Figure 5.19 and Figure 5.20.

Table 5.34 Hourly generation schedule

Hour	Thermal Generation (MW)			Hydro Generation (MW)			
	Unit 1	Unit 2	Unit 3	Plant1	Plant2	Plant3	Plant4
1	104.5349	213.9194	52.5021	78.3884	58.9585	51.5850	190.1116
2	23.7389	124.8637	229.5241	98.8278	51.5382	35.5494	215.9579
3	110.5720	126.4874	140.3742	59.1969	62.8926	0.0000	200.4770
4	20.8734	135.4939	139.7594	73.3007	82.4640	40.7033	157.4052
5	172.7179	124.8550	116.0016	94.5015	75.1120	0.0000	86.81210
6	42.1070	47.0501	319.1745	73.2992	57.1331	46.7910	214.4450
7	28.2881	292.1470	229.5765	53.2235	83.6220	49.0226	214.1202
8	102.6470	124.9429	408.9367	71.0240	46.8021	36.9300	218.7172
9	102.6619	209.8197	498.7306	59.9266	55.7711	50.1244	112.9657
10	102.5673	124.9935	498.6839	57.1097	57.8438	30.6379	208.1638
11	95.7874	119.2792	497.9670	53.4119	64.7836	43.1469	225.6240
12	102.5923	295.8326	341.1671	72.2967	65.1688	24.1536	248.7888
13	102.3479	124.5661	492.3114	70.2848	45.2413	49.9939	225.2545
14	174.4410	124.4387	317.8619	55.7801	64.3802	39.7841	253.3141
15	54.5977	212.9493	319.2539	89.6435	48.0449	51.5707	233.9401
16	174.5429	209.8348	277.1451	56.0091	71.9140	52.7268	217.8273
17	102.4081	209.9148	319.2779	67.6788	47.9687	48.2456	254.5060
18	174.9092	144.6462	319.2648	102.5408	52.9085	54.7691	270.9614
19	106.7570	209.9970	319.2450	77.1980	42.7598	48.5195	265.5237
20	157.6370	209.3998	229.4919	106.3851	47.4921	25.6605	273.9335
21	21.5086	209.7533	229.4640	89.2298	43.3937	53.6549	262.9958
22	102.6628	123.1305	229.6146	72.2401	59.6372	56.4012	216.3137
23	102.0376	123.4529	229.4981	72.0156	44.0318	53.9239	225.0401
24	25.2551	40.8884	229.6543	94.0021	73.1011	56.0885	281.0104

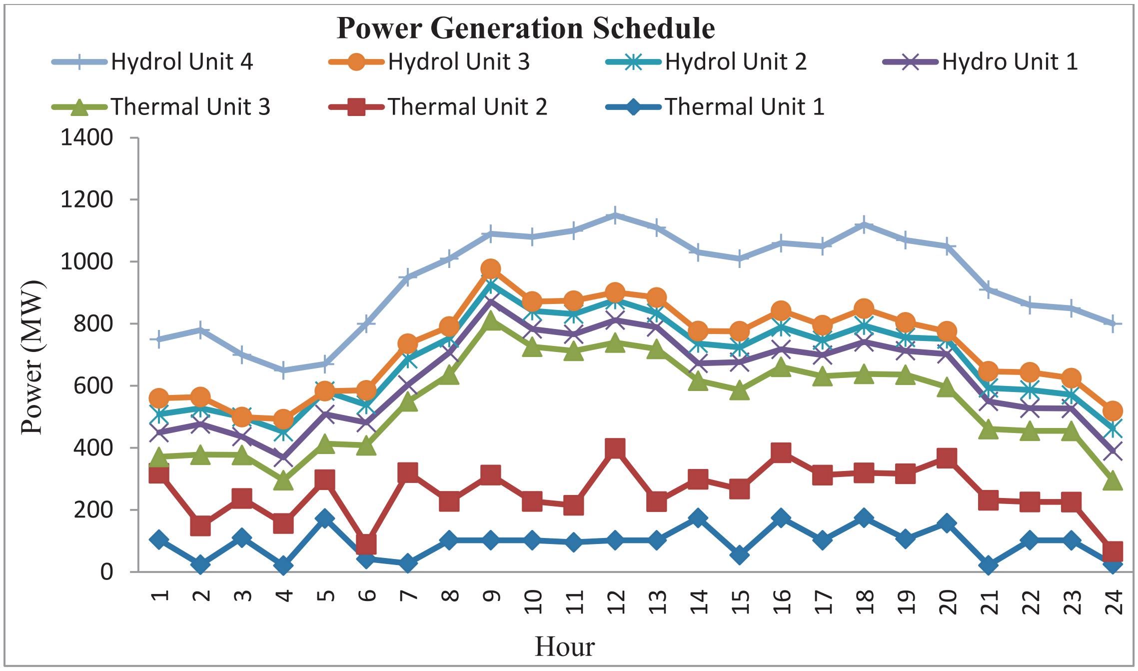

Figure 5.18 Hourly power generation schedule

Table 5.35 Hourly reservoir discharge

Hour	Reservoirs Discharge ($\times 10^4$ m^3)			
	Plant1	Plant2	Plant3	Plant4
1	8.4974	7.3604	18.1589	10.8334
2	14.2864	6.2693	21.3550	14.5779
3	5.9321	8.0161	28.5289	14.5513
4	7.7759	11.8850	17.5597	11.2331
5	12.7994	10.4507	29.3397	6.1233
6	8.2561	7.2791	12.7418	19.4521
7	5.3940	13.4994	12.3697	18.8102
8	7.7939	6.6713	20.0309	17.1621
9	6.1734	8.0372	16.0064	6.0222
10	5.6050	8.3884	21.0933	12.3348
11	5.0331	9.6313	18.3861	14.2389
12	7.2961	9.8255	21.9724	17.4437
13	6.8698	6.5041	11.2450	14.0477
14	5.1814	9.7458	18.8357	17.5242
15	9.6122	6.8382	13.9019	14.3294
16	5.1208	11.2094	14.4731	12.1325
17	6.3842	6.9428	16.6849	15.1208
18	11.9462	7.6889	11.9248	17.8545
19	7.5241	6.3290	17.4399	16.7857
20	13.4538	7.7874	22.6518	18.5983
21	9.4889	6.2716	10.8879	17.4957
22	7.1246	8.6802	13.1394	12.1054
23	7.0030	6.0638	16.8533	13.0765
24	10.3786	11.1785	10.3259	20.0680

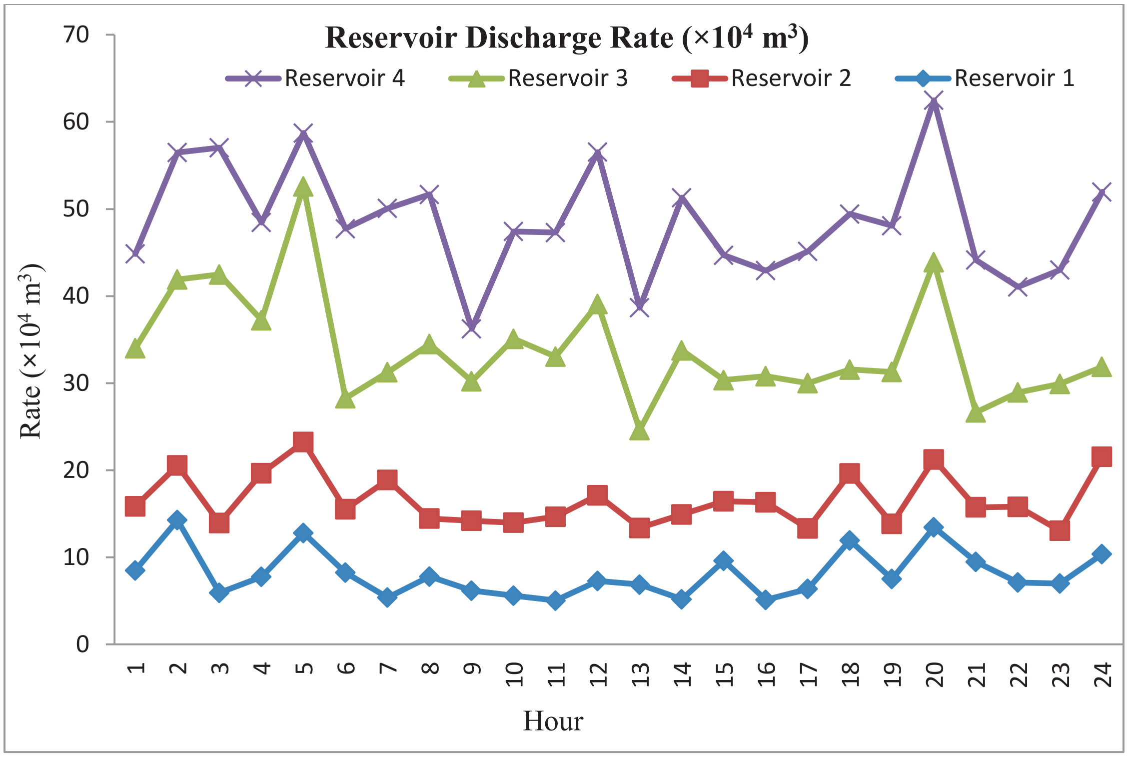

Figure 5.19 Hourly water discharge

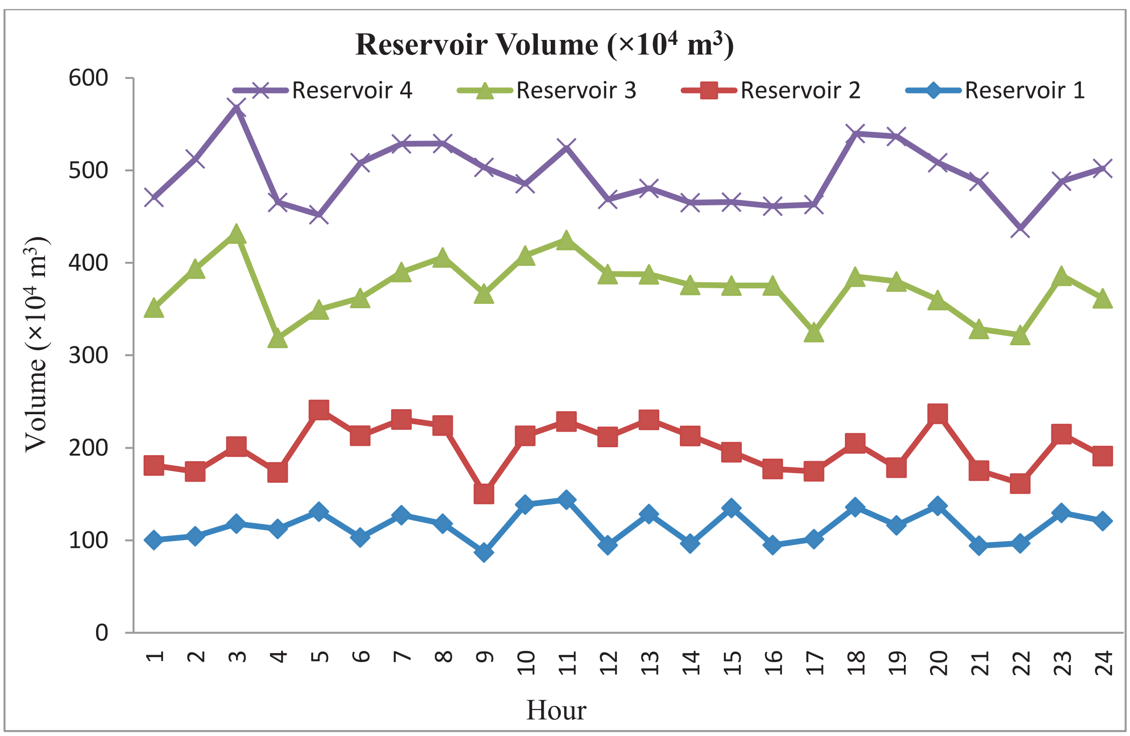

Figure 5.20 Hourly water volume

The value of the minimum cost function obtained is \$44736.15 with a standard deviation of \$2.77 and a range of \$20.19 between the minimum and maximum costs obtained. This cost is compared to those obtained using the Evolutionary Programming (EP) approach, the Simulated Annealing (SA) technique and the Particle Swarm Optimization (PSO) method [99]. This comparison is demonstrated in Table 5.36.

Table 5.36 Comparison of the cost function

Method	EP [99]	SA [99]	PSO [99]	MBFA
Cost (\$)	47306.00	45466.00	44740.00	44736.15
Average time (s)	9879.45	246.19	232.73	201.42

5.4.8 Case Study 4: Three Thermal and Four Hydro Plants, Valve-Point Effects and losses Considered

The same system in Case Study 3 is implemented with considering the transmission power losses of the system. The B-coefficients are given as follows [129]:

$$\mathbf{B} = 10^{-4}\begin{bmatrix} 0.34 & 0.13 & 0.09 & -0.01 & -0.08 & -0.01 & -0.02 \\ 0.13 & 0.14 & 0.10 & 0.01 & -0.05 & -0.02 & -0.01 \\ 0.09 & 0.10 & 0.31 & 0.00 & -0.11 & -0.07 & -0.05 \\ -0.01 & 0.01 & 0.00 & 0.24 & -0.08 & -0.04 & -0.07 \\ -0.08 & -0.05 & -0.11 & -0.08 & 1.92 & 0.27 & -0.02 \\ -0.01 & -0.02 & -0.07 & -0.04 & 0.27 & 0.32 & 0.00 \\ -0.02 & -0.01 & -0.05 & -0.07 & -0.02 & 0.00 & 1.35 \end{bmatrix} \tag{5.98}$$

$$\mathbf{B_0} = 10^{-6}\begin{bmatrix} -0.75 & -0.06 & 0.70 & -0.03 & 0.27 & -0.77 & -0.01 \end{bmatrix}, B_{00} = 0.55 \tag{5.99}$$

The MBFA is successfully applied to solve this problem considering both the valve-point effects and the power losses. The obtained minimum cost is \$41848.31 as shown in Table 5.37.

Table 5.37 Total cost and average time

Cost (\$)			Average time (sec)
Min	Max	Average	
41848.31	42877.37	42012.41	228.45

The optimal power generation schedule as well as the hourly transmission power losses over the scheduling period is shown in Table 5.38. This schedule is also illustrated in Figure 5.21. The water discharge rates at the end of each time interval are shown in Table 5.39 and Figure 5.22 while Figure 5.23 shows the water storage volume variations over the scheduling period.

Table 5.38 Hourly generation schedule, losses and demand

Hour	P_D (MW)	Thermal Generation (MW)			Hydro Generation (MW)				P_L (MW)
		Unit 1	Unit 2	Unit 3	Plant1	Plant2	Plant3	Plant4	
1	750	20.0499	219.0654	147.7282	81.5749	80.8289	49.2560	206.5789	55.0822
2	780	114.6358	226.4757	234.6085	82.6857	55.7456	0.0000	120.9157	55.0670
3	700	122.0478	234.7859	50.0147	116.2497	53.5183	52.8879	125.5432	55.0475
4	650	20.5699	227.2668	155.2999	97.5498	49.9734	18.6355	135.7519	55.0473
5	670	101.4100	76.6057	316.5588	70.1666	51.3131	0.0000	109.0055	55.0597
6	800	122.0872	213.2243	228.6456	87.6294	52.3461	26.9771	124.1559	55.0657
7	950	20.5459	296.6149	328.0640	94.2583	64.4223	40.6001	160.5909	55.0963
8	1010	103.7496	294.6958	247.8988	97.6768	61.7960	35.5585	223.7452	55.1207
9	1090	122.3309	293.5010	314.7387	70.7943	54.6653	47.1757	241.9418	55.1478
10	1080	121.3808	291.1188	247.4881	76.9508	53.9797	41.8766	302.3795	55.1743
11	1100	179.0880	291.3891	229.5320	87.0870	53.3791	33.4045	281.2869	55.1666
12	1150	52.4206	290.6620	320.8325	104.5772	91.0083	37.6320	308.0555	55.1881
13	1110	133.3164	206.4808	319.4077	93.8187	69.9316	41.5465	300.6771	55.1788
14	1030	179.9243	298.3692	234.2755	53.9330	70.0436	25.4944	223.0945	55.1345
15	1010	20.1425	208.6892	269.6520	183.6714	79.6531	0.0000	303.3518	55.1600
16	1060	149.0498	289.8256	228.1279	73.4684	93.8126	18.7773	262.0922	55.1538
17	1050	26.7746	298.0927	319.6868	62.5374	48.9094	44.4621	304.7137	55.1767
18	1120	134.0383	291.3512	317.2124	58.4072	50.1472	35.7881	288.2364	55.1809
19	1070	149.5447	293.4723	229.8906	52.9054	61.9889	45.5230	291.8453	55.1702
20	1050	49.6677	226.5137	322.3287	94.0969	58.8609	50.2351	303.4671	55.1701
21	910	109.7547	297.0556	69.6688	84.6895	73.9523	50.3847	279.6310	55.1366
22	860	101.3082	209.0077	95.1199	70.3836	86.4963	54.6910	298.1392	55.1459
23	850	20.8634	39.5311	316.2778	147.0106	84.2821	51.3121	245.8365	55.1136
24	800	20.0881	292.0858	78.6654	56.3104	78.6414	57.1856	272.1469	55.1237

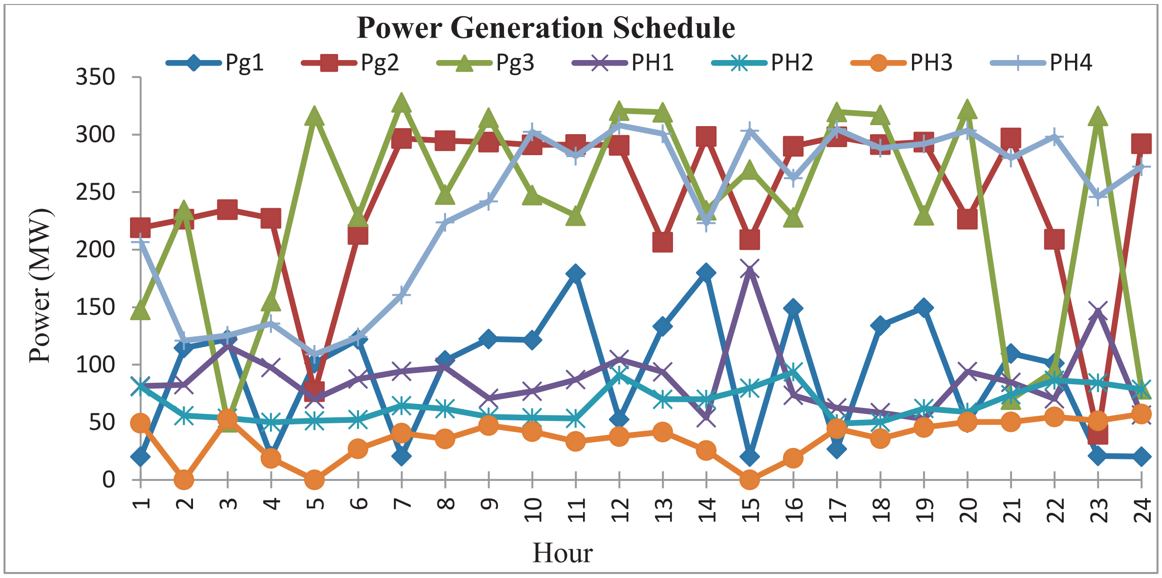

Figure 5.21 Hourly power generation schedule

Table 5.39 Hourly reservoir discharge

Hour	Reservoirs Discharge ($\times 10^4$ m^3)			
	Plant1	Plant2	Plant3	Plant4
1	9.5489	9.2315	28.9859	11.2315
2	6.2315	7.2144	14.2357	12.0215
3	6.4786	7.8563	26.2357	10.2316
4	6.0125	6.3322	12.3659	13.5247
5	6.2549	6.8746	26.3255	11.2326
6	5.2365	6.2155	15.3659	12.0215
7	6.2359	7.5649	15.2459	14.8789
8	7.5487	7.2146	16.3285	10.5466
9	8.3289	6.2357	15.3549	16.8887
10	6.2357	7.2146	13.2237	12.3256
11	5.8565	7.8799	13.0021	14.3257
12	5.2565	7.2365	17.2104	15.2155
13	6.9857	8.5699	13.5685	15.2316
14	7.2154	8.6589	13.0255	13.2356
15	5.4624	10.2357	18.1443	13.4880
16	9.3216	12.3257	9.8990	14.5846
17	8.3265	9.3256	28.1125	17.2385
18	5.2316	6.2316	28.9659	18.2365
19	6.2315	8.3256	10.4237	18.3257
20	12.2316	7.5685	10.2147	18.2315
21	10.2357	11.2386	11.8795	18.1255
22	6.3649	12.2326	11.2487	17.2346
23	12.4124	10.2356	12.8796	19.2352
24	6.5648	8.9866	25.0002	19.3256

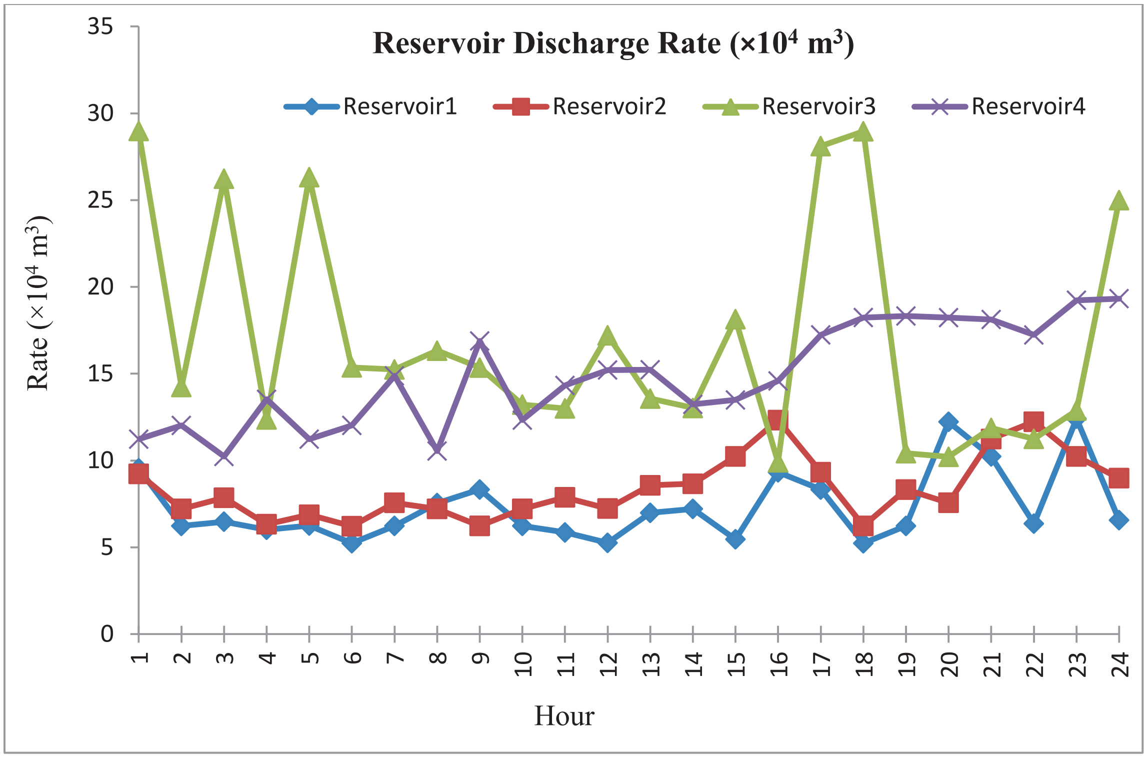

Figure 5.22 Hourly water discharge

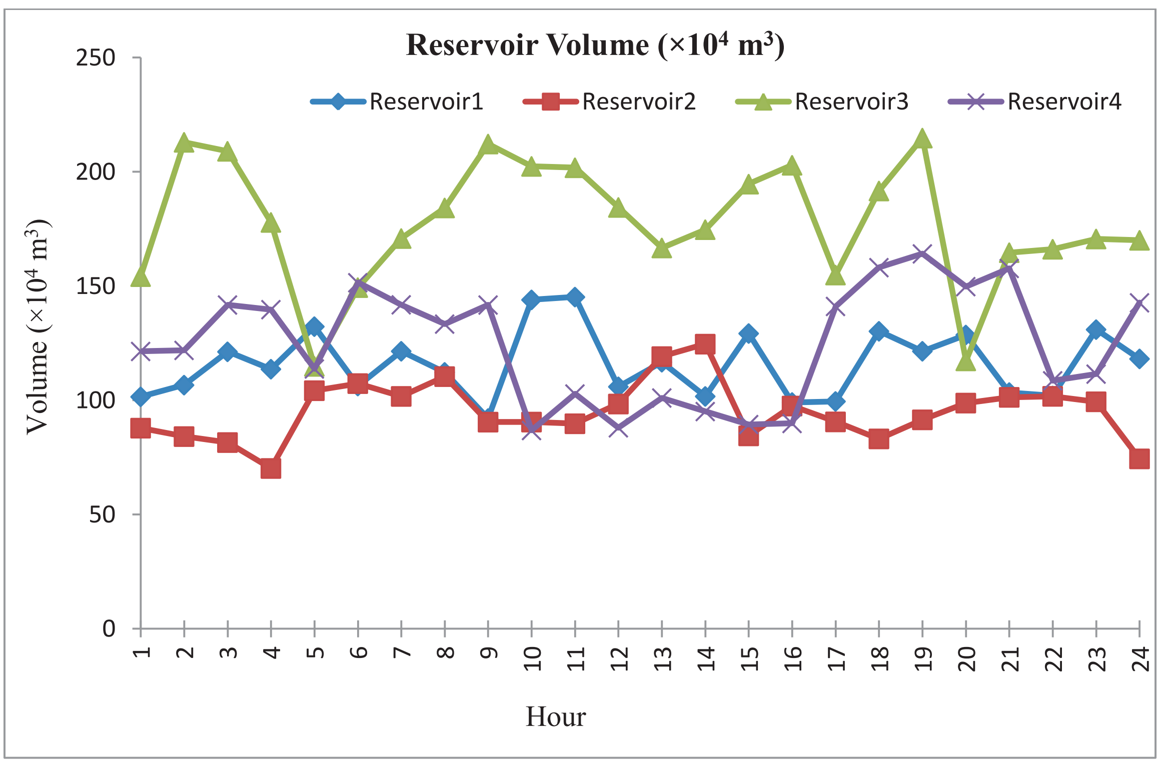

Figure 5.23 Hourly water volume

5.5 SUMMARY

In this chapter, the MBFA algorithm has been implemented to solve the short-term hydro-thermal generation scheduling problem. This economic dispatch problem is a dynamic optimization problem. Classifications of the problems in terms of their reservoirs and the availability of water has been presented and discussed. Various cases of hydro-thermal generation systems on separate streams and on the same streams with and without water head variations have been considered. In addition, multi-chains of cascaded reservoirs have also been studied. In each of these cases the problem is formulated and discussed in details. Various case study systems have been implemented considering a wide range of practical aspects such as the valve-point effects, transmission power losses and time delays associated with water inflow. Comparison of the obtained results with those reported in the literature whenever available has been shown. These results have demonstrated the effectiveness and capability of the proposed algorithm to solve this nonlinear complex problem in spite of the high dimensional search spaces and the non-smoothness of the characteristics.

CHAPTER 6 MULTI-OBJECTIVE ECONOMIC-EMISSION OPTIMIZATION FOR POWER GENERATION SYSTEMS

6.1 INTRODUCTION

The escalating demand for electric energy worldwide, has led to a significant increase in the electric power produced and the number of generation plants world-wide. Electrical power is generated using conventional and renewable sources including thermal, hydro, nuclear, wind, solar and marine-tidal energy. The major part of electric power is produced by thermal plants that use fossil-based fuels such as oil, coal and natural gas. Figure 6.1 shows the percentage of each fuel source used for power generation in the USA according to the electrical power monthly report issued in October 2011 [280] by the US Energy Information Administration [281].

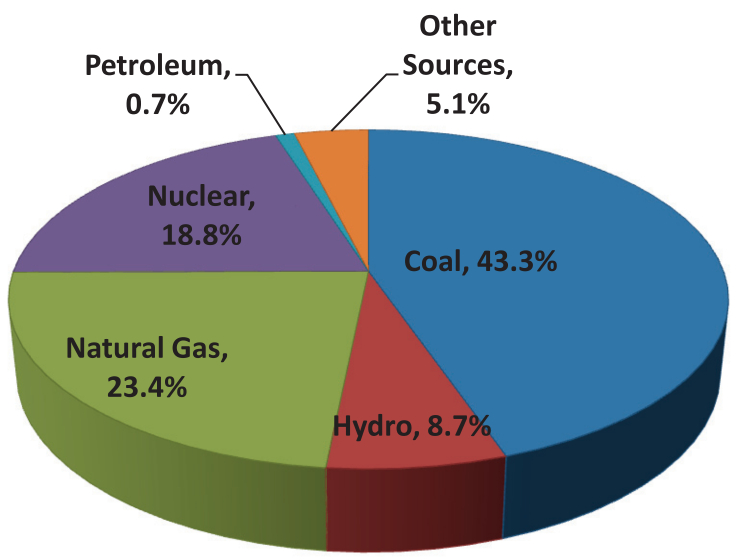

Figure 6.1 USA electrical power generation by energy source (July 2011)

The nature of thermal power generation plants that burn fossil-based fuel makes them among the main sources of gaseous emission and air pollution. Among the harmful gaseous emission that are produced by the fossil fuel combustion are; nitrogen oxides (NO_x), sulphur dioxide (SO_2) and carbon dioxide (CO_2). The harmful effects of these emissions on the environment have been well documented and are increasingly drawing great attention so that we can no longer overlook them. Accordingly, electric power generation and operation should be achieved not only at the lowest possible cost but also at the minimum feasible emission levels. In order to satisfy this goal, various regulations have been issued both nationally and internationally. In particular, the Clean Air Amendment of 1990 has become a mandatory operational guideline to control gaseous emission [4-8]. To meet these environmental regulations, various efforts have been made by applying several operational and planning strategies such as [138]:

- Treating the gases produced from combustion by applying enhanced design techniques to the combustion process furnaces. In addition, the combustion process itself is chemically treated so that the production of harmful gases is reduced.

- Using different types of fuel so that the emissions produced are reduced.

- Treating the gases produced by the combustion process by the installation of post-combustion filtering and scrubbing equipment.

- Considering the emission and environmental aspects as part of the load dispatch operations.

Among the options mentioned earlier, the last one, which is referred to as the economic-emission load dispatch, is favoured as there is no extra capital cost required. Besides, the economic-emission load dispatch is a short-range operational and planning practice that can be applied immediately [231].

In this chapter, the optimization problem of multi-objective economic-emission load dispatch is discussed, formulated and implemented using the proposed MBFA. The weighted-sum method, discussed in Chapter 3, is applied to solve several cases of multi-objective economic-emission dispatch problem of all-thermal generation systems. The short-term hydro-thermal generation scheduling problem is also treated in this chapter with the emission minimization objective considered. The proposed MBFA is applied to solve these multi-objective optimization problems using various cases and number of objectives.

6.2 ECONOMIC-EMISSION THERMAL GENERATION DISPATCH

The economic-emission dispatch for all-thermal power generation systems is formulated as a multi-objective optimization problem. As a result, the economic-emission dispatch problem considers four conflicting and non-commensurable objectives. Besides the fuel cost, these objectives are the NO_x, SO_2 and CO_2 emissions. Mathematically, these objective functions are expressed as follows [157]:

- The first objective, F_1 is the fuel cost function of the thermal generating units as expressed in Equations (4.1) and (4.3). This objective function is rewritten as:

$$F_1 = \sum_{i=1}^{N_g} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \quad \$/h \tag{6.1}$$

  The parameters a_i, b_i and c_i are the cost coefficients and N_g is the number of thermal generating units.

- The second objective, F_2 is the amount of NO_x emission modeled as a quadratic function of the output power of the generating units:

$$F_2 = \sum_{i=1}^{N_g} (d_{1i} P_{gi}^2 + e_{1i} P_{gi} + f_{1i}) \quad kg/h \tag{6.2}$$

  where d_{1i}, e_{1i} and f_{1i} are coefficients for the NO_x gaseous emission [282].

- The third objective, F_3 is the amount of SO_2 emission:

$$F_3 = \sum_{i=1}^{N_g} (d_{2i} P_{gi}^2 + e_{2i} P_{gi} + f_{2i}) \quad kg/h \tag{6.3}$$

  where d_{2i}, e_{2i} and f_{2i} are coefficients for the SO_2 emission [282].

- The fourth objective, F_4 is the amount of CO_2 emission:

$$F_4 = \sum_{i=1}^{N_g} (d_{3i} P_{gi}^2 + e_{3i} P_{gi} + f_{3i}) \quad kg/h \tag{6.4}$$

  where d_{3i}, e_{3i} and f_{3i} are coefficients for the CO_2 emission [172].

These objective functions are subject to various equality and inequality constraints as follows:

- Active power balance equality:

$$\sum_{i=1}^{N_g} P_{gi} - P_D - P_L = 0 \tag{6.5}$$

where P_D is the total load demand and P_L is the transmission power losses as a function of the real power generation. These losses are expressed using the *B*-coefficients [3]:

$$P_L = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{g_i} B_{ij} P_{g_j} + \sum_{i=1}^{N_g} B_{i0} P_{g_i} + B_{00} \tag{6.6}$$

- Generation capacity limits:

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, i = 1, 2, ..., N_g \tag{6.7}$$

Where $P_{gi}^{\min}$ and $P_{gi}^{\max}$ are the minimum and maximum generation limit of the i^{th} generating unit.

These conflicting and non-commensurable objective functions are minimized simultaneously to obtain non-inferior set of solutions to the multi-objective problem. Therefore, and according to Equation (3.3), the minimization problem is expressed as follows:

$$min \qquad [F_1(P_g), F_2(P_g), F_3(P_g), F_4(P_g)]^T \tag{6.8}$$

This multi-objective optimization problem is subject to various equality and inequality constraints stated above.

6.2.1 Weighted-Sum Method

The weighted-sum method [224], introduced in Section 3.3.3.1, is one of the widely applied techniques to solve multi-objective optimization problems. In order to apply this method, the multi-objective optimization problem is converted to a single one. Weights are assigned for each of the objectives according to the decision makers' preference. The values of these weighting factors reflect the relative importance of each of the conflicting objectives. The problem is expressed as follows [1]:

$$min \qquad \sum_{k=1}^{M} w_k F_k(P_{gi}) \tag{6.9}$$

subject to
$$\sum_{i=1}^{N_g} P_{gi} - P_D - P_L = 0 \tag{6.10}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, i = 1,2,...,N_g \tag{6.11}$$

$$\sum_{k=1}^{M} w_k = 1 \quad (w_k \ge 0) \tag{6.12}$$

where M is the number of objective functions and w_k is the weight assigned to the k^{th} objective.

6.2.2 *ε*–Constraint Method

In this method, as stated in Section 3.3.3.3, one of the objective functions is considered a primary one while the others are treated as constraints. Mathematically, this is expressed as follows [157]:

$$min \qquad [F_1(P_g)] \tag{6.13}$$

subject to
$$F_k(P_g) \le \varepsilon_k \qquad (k = 2,3,4) \tag{6.14}$$

$$\sum_{i=1}^{N_g} P_{gi} - P_D - P_L = 0 \tag{6.15}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, i = 1,2,...,N_g \tag{6.16}$$

where ε_k is the maximum tolerance for the k^{th} objective. The value of ε_k is chosen according to the impact of the k^{th} objective on the primary objective function $F_1(P_g)$.

6.2.3 Case Study: 6-Generator System Economic-Emission Dispatch

In this case study, the six-generator system, which was discussed in Section 4.5.2, is analyzed considering the four conflicting objectives. The load demand is 1800 MW and the coefficients for the fuel cost and emission equations are given in Table 6.1 [157]:

Table 6.1 Coefficients for cost and emission equations

Objective		Coefficient	Generator 1	2	3	4	5	6
Cost	F_1($/h)	a	0.002035	0.003866	0.002182	0.001345	0.002162	0.005963
		b	8.43205	6.41031	7.42890	8.30154	7.42890	6.91559
		c	85.6348	303.7780	847.1484	274.2241	847.1484	202.0258
NO_X	F_2(kg/h)	d_1	0.006323	0.006483	0.003174	0.006732	0.003174	0.006181
		e_1	-0.38128	-0.79027	-1.36061	-2.39928	-1.36061	-0.39077
		f_1	80.9019	28.8249	324.1775	610.2535	324.1775	50.3808
SO_2	F_3(kg/h)	d_2	0.001206	0.002320	0.001284	0.110813	0.001284	0.003578
		e_2	5.05928	3.84624	4.45647	4.97641	4.45647	4.14938
		f_2	51.3778	182.2605	508.5207	165.3433	508.5207	121.2133
CO_2	F_4(kg/h)	d_3	0.265110	0.140053	0.105929	0.106409	0.105929	0.403144
		e_3	-61.01945	-29.95221	-9.552794	-12.73642	-9.552794	-121.98120
		f_3	5080.148	3824.770	1342.851	1819.625	1342.851	11381.070

The B-coefficients matrix is the following:

$$B = 10^{-5}\begin{bmatrix} 20.0 & 1.0 & 1.5 & 0.5 & 0 & -3.0 \\ 1.0 & 30.0 & -2.0 & 0.1 & 1.2 & 1.0 \\ 1.5 & -2.0 & 10.0 & -1.0 & 1.0 & 0.8 \\ 0.5 & 0.1 & -1.0 & 15.0 & 0.6 & 5.0 \\ 0 & 1.2 & 1.0 & 0.6 & 25.0 & 2.0 \\ -3.0 & 1.0 & 0.8 & 5.0 & 2.0 & 21.0 \end{bmatrix} \tag{6.17}$$

The MBFA is implemented to solve this multi-objective problem considering various cases and different number of objective functions taking into consideration system losses. To generate the non-inferior solution for each case, the weighted-sum method is applied and implemented using the MBFA. In each case the Pareto optimal set of non-dominated solutions is obtained. The cases considered are as follows:

Case 1: Optimization of each of the four objectives individually.

Case 2: Optimization of fuel cost and NO_x emission.

Case 3: Optimization of fuel cost, NO_x emission and SO_2 emission.

Case 4: Optimization of fuel cost, NO_x emission, SO_2 emission and CO_2 emission.

6.2.3.1 Case 1: Individual Optimization of Cost and Emissions

In this case, the fuel cost, NO_x ,SO_2 and CO_2 emissions are minimized separately as single objective functions. Minimizing each objective function individually is executed by giving full weight to the function to be optimized and neglecting others. As a result, the minimum and maximum values for each function are determined. Results obtained for minimizing each of the four functions are shown in Table 6.2. The table shows the minimum objective function in each of the four individual optimization processes and the corresponding power generation dispatch. It also shows the resulting objective functions for the other three objectives according to the power generation level obtained by optimizing the forth objective.

Table 6.2 Individual minimization of each objective

	Min F_1 (\$/h)	Min F_2 (kg/h)	Min F_3 (kg/h)	Min F_4 (kg/h)
P_{g1} (MW)	252.314	198.536	251.830	246.1145927
P_{g2} (MW)	303.320	211.814	303.974	338.3301668
P_{g3} (MW)	503.094	538.274	505.530	379.5915598
P_{g4} (MW)	372.741	327.091	370.075	398.9112072
P_{g5} (MW)	301.329	476.825	302.981	338.3065614
P_{g6} (MW)	197.318	195.130	195.784	241.222651
P_{loss} (MW)	130.116	147.670	130.174	142.4767373
F_1 (\$/h)	**18721.390**	18950.609	18721.456	18807.918
F_2 (kg/h)	2298.434	**2077.820**	2294.712	2424.912
F_3 (kg/h)	11222.989	11356.338	**11222.956**	11277.212
F_4 (kg/h)	60522.875	66911.032	60576.573	**58144.545**

6.2.3.2 Case 2: Bi-Objective Optimization of Cost and NO_x Emission

In this case, for the same system, only the NO_x emission is considered in addition to the fuel cost objective. The bi-objective optimization problem is converted into a single one by using the weighting factors. The non-inferior solution set is obtained using the MBFA and presented in Table 6.3. As shown in the table, the maximum and minimum values of w_1 and w_2 represent the two ends of the Pareto optimal front as illustrated in Figure 6.2. The power generation level of each unit corresponding to each of the non-dominated solutions is shown in Table 6.4.

It is clearly noticeable that any decrease in emission results in an increase in the fuel cost which is obvious as the two objectives are conflicting and non-commensurable.

Table 6.3 Non-dominant solutions for cost and NO_x objectives

Solution Number	Weight		Objective	
	w_1	w_2	F_1 (\$/h)	F_2 (kg/h)
1	1.0	0.0	18721.390	2298.434
2	0.9	0.1	18723.550	2267.395
3	0.8	0.2	18729.751	2222.914
4	0.7	0.3	18738.556	2194.273
5	0.6	0.4	18751.461	2168.296
6	0.5	0.5	18779.870	2132.546
7	0.4	0.6	18805.238	2113.397
8	0.3	0.7	18826.364	2101.754
9	0.2	0.8	18865.967	2087.972
10	0.1	0.9	18914.310	2079.872
11	0.0	1.0	18950.609	2077.820

Table 6.4 Power generation dispatch and losses

Solution Number	Power Generation Dispatch						P_{loss} (MW)
	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{g4} (MW)	P_{g5} (MW)	P_{g6} (MW)	
1	252.314	303.320	503.094	372.741	301.329	197.318	130.116
2	243.861	305.498	501.546	363.872	320.036	196.869	131.683
3	237.792	286.720	509.591	365.819	334.511	197.182	131.615
4	233.377	280.940	515.824	356.547	348.851	196.947	132.486
5	233.171	271.444	515.499	358.361	357.109	197.264	132.848
6	222.588	256.628	524.778	348.255	387.935	195.363	135.546
7	220.043	249.337	528.527	338.472	406.637	194.555	137.571
8	212.001	239.617	531.070	340.540	416.487	199.088	138.804
9	204.787	233.982	532.202	334.833	441.375	195.100	142.279
10	203.103	220.270	531.281	334.469	464.235	192.199	145.558
11	198.536	211.814	538.274	327.091	476.825	195.130	147.670

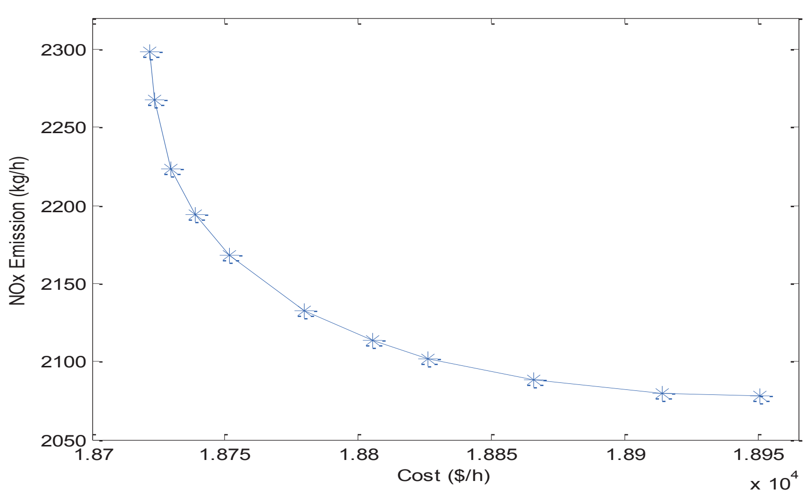

Figure 6.2 Pareto optimal front for cost and NO_x objectives

6.2.3.3 Case 3: Optimization of Cost, NO_x and SO_2 Emission

A third objective, which is the SO_2 emission, is considered in this case in addition to the fuel cost and the NO_x emission. Three weighting factors are applied to convert this multi-objective optimization problem to a single one using the weighted-sum method. These weights as well as the set of the non-dominated solutions are shown in Table 6.5 while the power generation level associated to this set is presented in Table 6.6.

Table 6.5 Non-dominant solutions for cost, NO_x and SO_2 objectives

Solution No.	Weight			Objective		
	w_1	w_2	w_3	F_1 (\$/h)	F_2 (kg/h)	F_3 (kg/h)
1	1.00	0.00	0.00	18721.390	2298.434	11222.989
2	0.85	0.15	0.00	18726.186	2240.531	11225.405
3	0.70	0.30	0.00	18738.556	2194.273	11232.280
4	0.55	0.45	0.00	18767.061	2146.534	11248.647
5	0.40	0.60	0.00	18805.238	2113.397	11270.880
6	0.25	0.75	0.00	18848.252	2094.135	11296.349
7	0.10	0.90	0.00	18914.310	2079.872	11335.028
8	0.85	0.00	0.15	18721.541	2297.449	11223.025
9	0.70	0.15	0.15	18728.486	2227.704	11226.633
10	0.55	0.30	0.15	18747.226	2175.518	11237.244
11	0.40	0.45	0.15	18772.099	2140.147	11251.559
12	0.25	0.60	0.15	18814.925	2107.686	11276.627
13	0.10	0.75	0.15	18871.341	2086.714	11309.665
14	0.70	0.00	0.30	18721.727	2287.847	11223.012
15	0.55	0.15	0.30	18728.728	2226.774	11226.655
16	0.40	0.30	0.30	18748.066	2173.860	11237.628
17	0.25	0.45	0.30	18779.070	2133.373	11255.723
18	0.10	0.60	0.30	18825.309	2102.192	11282.665
19	0.55	0.00	0.45	18721.489	2290.226	11223.017
20	0.40	0.15	0.45	18729.263	2224.086	11227.017
21	0.25	0.30	0.45	18750.146	2170.022	11238.907
22	0.10	0.45	0.45	18787.209	2126.110	11260.382
23	0.40	0.00	0.60	18721.751	2290.956	11223.088
24	0.25	0.15	0.60	18729.389	2223.841	11227.118
25	0.10	0.30	0.60	18755.842	2161.025	11242.254
26	0.25	0.00	0.75	18722.732	2286.163	11223.570
27	0.10	0.15	0.75	18730.660	2219.319	11227.748
28	0.10	0.00	0.90	18721.478	2299.679	11223.023

Table 6.6 Power generation dispatch and losses

Solution No.	Power Generation Dispatch						P_{loss} (MW)
	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{g4} (MW)	P_{g5} (MW)	P_{g6} (MW)	
1	252.314	303.320	503.094	372.741	301.329	197.318	130.116
2	244.135	291.942	506.361	365.768	328.079	195.051	131.337
3	233.377	280.940	515.824	356.547	348.851	196.947	132.486
4	230.588	260.812	524.078	344.610	376.416	197.783	134.286
5	220.043	249.337	528.527	338.472	406.637	194.555	137.571
6	213.485	236.459	519.684	339.523	434.641	197.540	141.332
7	203.103	220.270	531.281	334.469	464.235	192.199	145.558
8	255.921	302.216	504.370	370.226	301.831	195.413	129.978
9	238.380	289.798	511.716	360.259	331.051	200.241	131.445
10	230.665	274.264	519.048	349.798	357.857	201.428	133.060
11	223.103	261.146	526.609	345.751	381.010	197.285	134.904
12	212.297	242.110	531.128	344.172	408.427	199.682	137.815
13	207.100	227.099	535.711	337.513	440.553	193.918	141.895
14	250.915	299.711	510.362	368.561	302.025	198.162	129.735
15	241.519	288.726	515.617	358.092	330.849	196.377	131.179
16	229.217	274.541	523.313	350.751	358.597	196.605	133.024
17	221.499	258.374	521.865	349.210	388.732	196.108	135.787
18	213.710	240.303	531.352	340.621	416.649	196.111	138.746
19	250.094	301.461	503.695	372.158	304.190	198.606	130.204
20	237.982	287.039	514.885	361.047	331.033	199.228	131.213
21	229.085	270.583	520.672	354.677	360.639	197.465	133.121
22	221.073	255.418	526.994	340.600	393.141	198.943	136.168
23	256.765	300.870	504.465	368.325	305.089	194.573	130.086
24	236.769	286.755	514.210	362.360	331.054	200.103	131.251
25	229.650	268.680	517.872	349.249	368.115	200.317	133.883
26	245.125	294.737	515.289	378.048	299.207	196.835	129.241
27	238.084	283.502	517.945	363.292	332.279	195.927	131.029
28	251.032	302.371	506.342	373.498	298.663	197.909	129.815

6.2.3.4 Case 4: Optimization of Four Objectives

In this final case, the four emission objectives are taken into consideration. These are the fuel cost, NO_x , SO_2 and CO_2 emission. A weighting factor is assigned for each objective function so that the problem is converted into a single-objective optimization one. The obtained non-dominated solutions and the load dispatch are shown in Table 6.7 and Table 6.8 respectively.

Table 6.7 Non-dominant solutions for cost, NO_x, SO_2 and CO_2 objectives

Solution No.	Weight				Objective			
	w_1	w_2	w_3	w_4	F_1 (\$/h)	F_2 (kg/h)	F_3 (kg/h)	F_4 (kg/h)
1	1.00	0.00	0.00	0.00	18721.390	2298.434	11222.989	60522.875
2	0.70	0.30	0.00	0.00	18738.556	2194.273	11232.280	61044.914
3	0.40	0.60	0.00	0.00	18805.238	2113.397	11270.880	63019.370
4	0.10	0.90	0.00	0.00	18914.310	2079.872	11335.028	65842.077
5	0.70	0.00	0.30	0.00	18721.727	2287.847	11223.012	60687.283
6	0.40	0.30	0.30	0.00	18748.066	2173.860	11237.628	61497.540
7	0.10	0.60	0.30	0.00	18825.309	2102.192	11282.665	63579.499
8	0.40	0.00	0.60	0.00	18721.751	2290.956	11223.088	60624.685
9	0.10	0.30	0.60	0.00	18755.842	2161.025	11242.254	61395.530
10	0.10	0.00	0.90	0.00	18721.478	2299.679	11223.023	60581.404
11	0.70	0.00	0.00	0.30	18778.282	2367.771	11258.867	58088.035
12	0.40	0.30	0.00	0.30	18778.413	2349.241	11258.758	58100.385
13	0.10	0.60	0.00	0.30	18777.110	2332.417	11257.871	58128.872
14	0.40	0.00	0.30	0.30	18778.361	2347.666	11258.745	58108.461
15	0.10	0.30	0.30	0.30	18781.114	2346.541	11260.403	58098.860
16	0.10	0.00	0.60	0.30	18780.410	2370.193	11260.182	58081.746
17	0.40	0.00	0.00	0.60	18783.827	2380.362	11262.304	58075.585
18	0.10	0.30	0.00	0.60	18788.524	2355.071	11264.929	58082.799
19	0.10	0.00	0.30	0.60	18782.288	2379.640	11261.375	58080.522
20	0.10	0.00	0.00	0.90	18786.579	2379.323	11263.916	58073.358

Table 6.8 Power generation dispatch and losses

Solution No.	Power Generation Dispatch						P_{loss} (MW)
	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{g4} (MW)	P_{g5} (MW)	P_{g6} (MW)	
1	252.314	303.320	503.094	372.741	301.329	197.318	130.116
2	233.377	280.940	515.824	356.547	348.851	196.947	132.486
3	220.043	249.337	528.527	338.472	406.637	194.555	137.571
4	203.103	220.270	531.281	334.469	464.235	192.199	145.558
5	250.915	299.711	510.362	368.561	302.025	198.162	129.735
6	229.217	274.541	523.313	350.751	358.597	196.605	133.024
7	213.710	240.303	531.352	340.621	416.649	196.111	138.746
8	256.765	300.870	504.465	368.325	305.089	194.573	130.086
9	229.650	268.680	517.872	349.249	368.115	200.317	133.883
10	251.032	302.371	506.342	373.498	298.663	197.909	129.815
11	249.000	330.698	404.525	382.039	339.498	234.154	139.914
12	248.953	328.842	406.068	375.872	347.964	232.598	140.296
13	249.090	320.897	407.234	377.795	352.072	232.891	139.980
14	248.772	325.605	403.736	383.157	349.665	229.382	140.317
15	249.327	324.588	401.978	381.371	351.140	232.091	140.494
16	250.189	329.609	401.765	383.482	340.073	234.920	140.036
17	249.641	333.562	398.350	385.521	340.401	233.116	140.590
18	247.470	328.452	397.653	379.141	352.551	236.031	141.297
19	252.721	331.476	398.549	384.687	339.152	233.647	140.233
20	248.807	336.638	397.656	381.381	343.730	232.933	141.145

The results obtained from the various cases demonstrated in this section show the ability of the MBFA to solve the economic-emission load dispatch as a multi-objective optimization problem effectively and obtain the non-inferior solutions. The algorithm is successfully applied to capture the shape of the Pareto optimal front for any number of objectives and for various fuel qualities.

6.3 ECONOMIC-EMISSION SHORT-TERM HYDRO-THERMAL GENERATION SCHEDULING

The fixed-head short-term hydro-thermal generation scheduling discussed in Section 5.2 as a single objective optimization problem is considered here. This problem is treated as a multi-objective problem where emission objectives are optimized along with the cost objective function. Operating cost of thermal generating units, NO_x, SO_2 and CO_2 emissions are minimized over the scheduling period considering various thermal and hydraulic constraints.

6.3.1 Problem Formulation

The cost and emission objectives of the fixed-head short-term hydro-thermal generation scheduling problem are mathematically expressed as follows [128, 283]:

$$F_1 = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k (a_i P_{gi_k}^2 + b_i P_{gi_k} + c_i) \ \ \$ \tag{6.18}$$

$$F_2 = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k (d_{1i} P_{gi_k}^2 + e_{1i} P_{gi_k} + f_{1i}) \ \ kg \tag{6.19}$$

$$F_3 = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k (d_{2i} P_{gi_k}^2 + e_{2i} P_{gi_k} + f_{2i}) \ \ kg \tag{6.20}$$

$$F_4 = \sum_{k=1}^{N_k} \sum_{i=1}^{N_g} n_k (d_{3i} P_{gi_k}^2 + e_{3i} P_{gi_k} + f_{3i}) \ \ kg \tag{6.21}$$

subject to

$$\sum_{i=1}^{N_g} P_{gi_k} + \sum_{j=1}^{M_H} P_{Hj_k} - P_{D_k} - P_{L_k} = 0 \tag{6.22}$$

$$P_{gi_k}^{\min} \le P_{gi_k} \le P_{gi_k}^{\max}, \quad P_{Hj_k}^{\min} \le P_{Hj_k} \le P_{Hj_k}^{\max} \tag{6.23}$$

$$\sum_{k=1}^{N_k} n_k q_{j_k} = V_j \tag{6.24}$$

where

F_1 : cost function of thermal units over the total scheduling time intervals N_k

F_2 : NO_x emission objective function over the total scheduling time intervals N_k

F_3 : SO_2 emission objective function over the total scheduling time intervals N_k

F_4 : CO_2 emission objective function over the total scheduling time intervals N_k

N_k : number scheduling time intervals

n_k : number of hours in scheduling time interval k

a_i, b_i, c_i : cost coefficients of the i^{th} thermal generating unit

d_{1i}, e_{1i}, f_{1i} : NO_x emission coefficients

d_{2i}, e_{2i}, f_{2i} : SO_2 emission coefficients

d_{3i}, e_{3i}, f_{3i} : CO_2 emission coefficients

P_{gi_k} : power generation of thermal unit i at time interval k

P_{Hj_k} : power generation of hydro unit j at time interval k

P_{D_k} : total demand during the time interval k

P_{L_k} : total transmission power losses during the time interval k

$P_{gi}^{\min}$: minimum power generation for thermal generating unit i

$P_{gi}^{\max}$: maximum power generation for thermal generating unit i

$P_{Hj}^{\min}$: minimum power generation for hydro generating unit j

$P_{Hj}^{\max}$: maximum power generation for hydro generating unit j

Applying the weighted-sum method, the Pareto optimal set of solutions is obtained by converting the multi-objective optimization problem into a single one. This is expressed as follows [128, 283]:

$$min \qquad \sum_{k=1}^{M} w_k F_k (P_{gi}) \tag{6.25}$$

where M is the number of objective functions and w_k is the weight assigned to the k^{th} objective. In addition to the constraints expressed in Equations (6.22), (6.23) and (6.24), this multi-objective problem is subject to:

$$\sum_{k=1}^{M} w_k = 1 \quad (w_k \geq 0) \tag{6.26}$$

6.3.2 Case Study: Two Thermal and Two Hydro Plants

A hydro-thermal generation system of two thermal and two hydro plants is considered [1, 128, 283]. The characteristics equations for the fuel cost, NO_x , SO_2 and CO_2 emission of the thermal generating units are given in Table 6.9.

Table 6.9 Coefficients for cost and emission equations

			Generator	
Objective		Coefficient	1	2
Cost	F_1($/h)	a	0.0025	0.0008
		b	3.20	3.40
		c	25.00	30.00
NO_X	F_2(kg/h)	d_1	0.006483	0.006483
		e_1	-0.79027	-0.79027
		f_1	28.82488	28.82488
SO_2	F_3(kg/h)	d_2	0.00232	0.00232
		e_2	3.84632	3.84632
		f_2	182.2605	182.2605
CO_2	F_4(kg/h)	d_3	0.084025	0.084025
		e_3	-2.944584	-2.944584
		f_3	137.7043	137.7043

The hourly load demand for each time interval over the scheduling period is given in Table 6.10, and the B-coefficient matrix is given as:

$$\mathbf{B} = 10^{-4}\begin{bmatrix} 1.40 & 0.10 & 0.15 & 0.15 \\ 0.10 & 0.60 & 0.10 & 0.13 \\ 0.15 & 0.10 & 0.68 & 0.65 \\ 0.15 & 0.13 & 0.65 & 0.70 \end{bmatrix} \tag{6.27}$$

Table 6.10 Load demand for each scheduling interval

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	400	7	450	13	1200	19	1330
2	300	8	900	14	1250	20	1250
3	250	9	1230	15	1250	21	1170
4	250	10	1250	16	1270	22	1050
5	250	11	1350	17	1350	23	900
6	300	12	1400	18	1470	24	600

Water discharge rates of the two hydro plants, as defined in Equation (5.24), are given as:

$$q_{1_k} = 6.1160\times10^{-6} P_{H1_k}^2 + 0.00866494 P_{H1_k} + 0.05606727\, M.m^3/h \tag{6.28}$$

$$q_{2_k} = 1.0194\times10^{-5} P_{H2_k}^2 + 0.01732988 P_{H2_k} + 0.02650452\, M.m^3/h \tag{6.29}$$

The volume of water available for the first hydro plant is 71.0 $M.m^3$ and for the second is 60.0 $M.m^3$.

The MBFA is applied to solve this multi-objective problem considering various cases and number of objectives. To obtain the Pareto optimal front for each case, the weighted-sum method is applied and implemented. In each case, the non-dominated set of solutions is presented. The cases that are considered are as follows:

Case 1: Optimization of each of the four objectives individually.

Case 2: Optimization of fuel cost and NO_x emission.

Case 3: Optimization of fuel cost, NO_x emission and SO_2 emission.

Case 4: Optimization of fuel cost, NO_x emission, SO_2 emission and CO_2 emission.

6.3.2.1 Case 1: Individual Optimization of Cost and Emissions

In this case, every one of the four objectives; the fuel cost, the NO_x, SO_2 and CO_2 emission, is minimized as a single objective function. Results obtained are shown in Table 6.11. The table shows the minimum objective function in each of the four individual optimization processes and the resulting objective functions for the other three objectives. The corresponding hourly optimal power schedule is presented in Table 6.12.

Table 6.11 Individual minimization of each objective

	Min F_1 ($)	Min F_2 (kg)	Min F_3 (kg)	Min F_4 (kg)
F_1 ($)	**52753.291**	55828.427	54762.238	55784.252
F_2 (kg)	22803.775	**19932.248**	20978.468	19987.685
F_3 (kg)	72355.712	72287.658	**71988.754**	72133.264
F_4 (kg)	383106.467	337846.583	374222.436	**334231.219**

Table 6.12 Hourly generation schedule and losses (corresponding to minimizing F_1)

Hour	Generation (MW)				P_L
	Thermal		Hydro		
	Plant 1	Plant 2	Plant 1	Plant 2	(MW)
1	114.6211	92.5124	114.8320	84.3537	6.3192
2	91.8189	137.1296	64.7878	9.6139	3.3502
3	90.7484	65.5300	82.4644	13.8041	2.5470
4	94.2215	64.5400	87.8323	6.0049	2.5988
5	81.5023	86.7014	76.3111	7.8413	2.3562
6	102.7642	101.8882	79.6211	19.2108	3.4843
7	125.0102	195.0400	132.7695	4.4707	7.2905
8	228.1895	203.1860	241.0032	261.0060	33.3848
9	278.0181	459.4646	345.6354	203.2548	56.3729
10	271.4043	463.0400	385.5052	188.2715	58.2210
11	317.7566	508.8605	412.9773	178.9734	68.5678
12	317.4754	519.8706	428.8553	207.8804	74.0817
13	246.1135	412.5979	362.4100	233.2205	54.3419
14	378.8812	493.5207	272.4080	166.3229	61.1328
15	291.8768	528.4683	315.4877	171.7760	57.6087
16	374.7779	424.5901	294.6237	239.9567	63.9484
17	295.7679	508.8484	405.8898	207.8021	68.3082
18	348.8727	556.8631	439.4227	206.9816	82.1401
19	304.4022	484.8203	384.3609	223.2202	66.8037
20	201.7052	545.2475	411.2643	148.4756	56.6926
21	271.8560	425.6737	281.0225	242.6899	51.2421
22	255.2870	413.3101	275.4704	146.4007	40.4683
23	241.6340	198.4806	347.8077	145.5747	33.4971
24	161.1801	172.0311	260.2474	20.1665	13.6251

6.3.2.2 Case 2: Bi-Objective Optimization of Cost and NO_x Emission

Fuel cost and NO_x emission are the two objectives to be minimized simultaneously in the bi-objective problem considered in this case. The set of solutions obtained for various weighting combinations are tabulated in Table 6.13, and the Pareto optimal front is depicted in Figure 6.3.

Table 6.13 Non-dominant solutions for cost and NO_x objectives (case 2)

Solution Number	Weight		Objective	
	w_1	w_2	F_1 ($)	F_2 (kg)
1	1.0	0.0	52753.291	22803.775
2	0.9	0.1	52791.424	22646.452
3	0.8	0.2	52864.575	22264.758
4	0.7	0.3	52997.479	22251.424
5	0.6	0.4	53674.259	21768.452
6	0.5	0.5	54011.424	21324.483
7	0.4	0.6	54876.785	20864.758
8	0.3	0.7	55137.478	20545.265
9	0.2	0.8	55335.249	20391.549
10	0.1	0.9	55642.429	20015.000
11	0.0	1.0	55828.427	19932.248

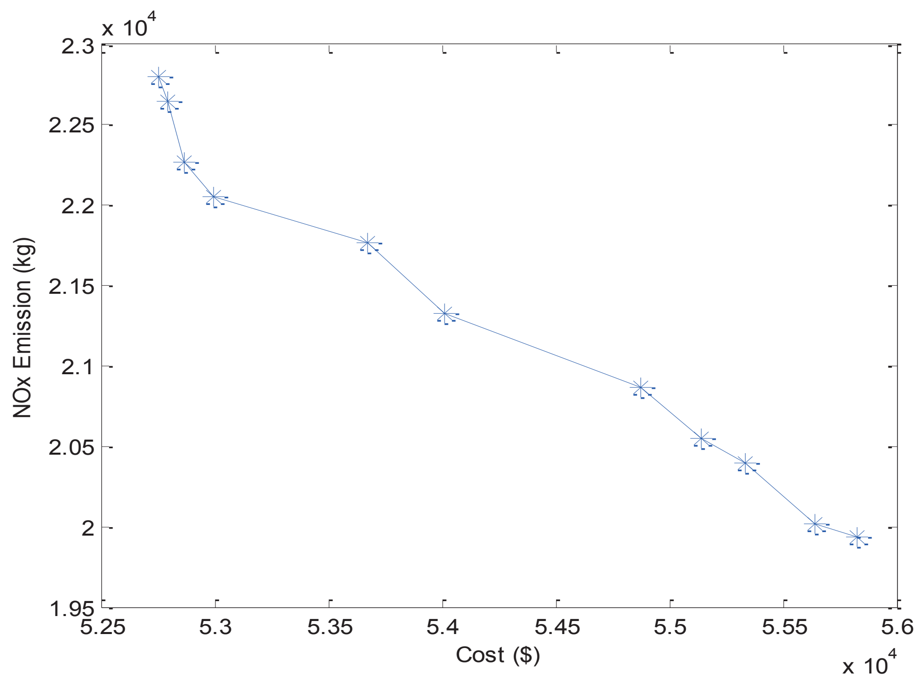

Figure 6.3 Pareto optimal front for cost and NO_x objectives (case 2)

6.3.2.3 Case 3: Optimization of Cost, NO_x and SO_2 Emission

Three objectives are treated in this case. These are; NO_x and SO_2 emission in addition to the fuel cost. Non-inferior solutions are obtained using various weight combinations. Results are shown in Table 6.14 along with the assigned weighting factors.

Table 6.14 Non-dominant solutions for cost and NO_x objectives (case 3)

Solution Number	Weight			Objective		
	w_1	w_2	w_3	F_1 (\$)	F_2 (kg)	F_3 (kg)
1	1.00	0.00	0.00	52753.291	22803.775	72355.712
2	0.85	0.15	0.00	52823.424	22618.468	72146.476
3	0.70	0.30	0.00	52997.479	22251.424	72176.488
4	0.55	0.45	0.00	53998.848	21778.255	72203.348
5	0.40	0.60	0.00	54876.785	20864.758	72248.424
6	0.25	0.75	0.00	55113.365	20346.688	72285.424
7	0.10	0.90	0.00	55642.429	20015.000	72301.548
8	0.85	0.00	0.15	52411.274	23864.486	72445.739
9	0.70	0.15	0.15	52594.414	23122.458	72231.877
10	0.55	0.30	0.15	53617.329	22014.548	72243.466
11	0.40	0.45	0.15	53875.642	21887.655	72231.678
12	0.25	0.60	0.15	54822.625	21042.456	72239.146
13	0.10	0.75	0.15	55408.743	20179.342	72324.856
14	0.70	0.00	0.30	51878.475	24857.649	72355.145
15	0.55	0.15	0.30	52665.430	22891.476	72314.445
16	0.40	0.30	0.30	53295.875	22136.425	72162.315
17	0.25	0.45	0.30	54569.474	21521.436	72214.322
18	0.10	0.60	0.30	55224.436	20303.563	72381.413
19	0.55	0.00	0.45	52464.756	23823.434	72187.657
20	0.40	0.15	0.45	52621.524	22912.433	722032.459
21	0.25	0.30	0.45	54371.429	21631.235	72214.375
22	0.10	0.45	0.45	54741.743	21401.874	72341.285
23	0.40	0.00	0.60	52522.419	23642.865	72384.762
24	0.25	0.15	0.60	52587.488	23335.125	72161.225
25	0.10	0.30	0.60	54774.275	21341.543	72154.412
26	0.25	0.00	0.75	53807.643	21989.255	72128.548
27	0.10	0.15	0.75	54773.452	21294.625	72131.463
28	0.10	0.00	0.90	54811.549	21177.424	72018.488

6.3.2.4 Case 4: Optimization of Four Objectives

The four objectives, which are the fuel cost, NO_x, SO_2 and CO_2 emission, are considered in this case. A combination of four weights is applied each time to obtain the set of non-dominated solutions as shown in Table 6.15.

Table 6.15 Non-dominant solutions for cost, NO_x, SO_2 and CO_2 objectives

Solution	Weight				Objective			
No.	w_1	w_2	w_3	w_4	F_1 ($)	F_2 (kg)	F_3 (kg)	F_4 (kg)
1	1.00	0.00	0.00	0.00	52753.291	22803.775	72355.712	383106.467
2	0.70	0.30	0.00	0.00	52997.479	22251.424	72336.488	372854.232
3	0.40	0.60	0.00	0.00	54876.785	20864.758	72242.424	354512.426
4	0.10	0.90	0.00	0.00	55642.429	20015.000	72201.548	351444.615
5	0.70	0.00	0.30	0.00	51878.475	24857.649	72455.145	387506.232
6	0.40	0.30	0.30	0.00	53295.875	22136.425	72322.315	367475.643
7	0.10	0.60	0.30	0.00	55224.436	20303.563	72381.413	352245.218
8	0.40	0.00	0.60	0.00	52522.419	23642.865	72384.762	384542.254
9	0.10	0.30	0.60	0.00	54774.275	21341.543	72154.412	357577.563
10	0.10	0.00	0.90	0.00	54811.549	21177.424	72018.488	355214.215
11	0.70	0.00	0.00	0.30	55037.275	20883.423	72342.514	352242.385
12	0.40	0.30	0.00	0.30	55163.241	20851.812	72274.414	352111.254
13	0.10	0.60	0.00	0.30	55296.419	20832.155	72312.546	352223.549
14	0.40	0.00	0.30	0.30	54974.769	20863.215	72382.215	352256.541
15	0.10	0.30	0.30	0.30	55263.216	20841.421	72362.215	352238.453
16	0.10	0.00	0.60	0.30	55214.362	20845.414	72354.142	352214.715
17	0.40	0.00	0.00	0.60	55198.473	20845.215	72374.235	352224.542
18	0.10	0.30	0.00	0.60	55232.422	20829.958	72354.242	352214.521
19	0.10	0.00	0.30	0.60	55250.864	20841.413	72363.241	352265.413
20	0.10	0.00	0.00	0.90	55244.136	20844.431	72352.125	352278.379

Results obtained in this case study show the effectiveness of the MBFA in solving this large-scale multi-objective optimization problem and finding optimal or close to optimal solution. These solutions are represented in the set of non-inferior points on the trade-off curve obtained in each case for the assigned weighting factors.

6.4 SUMMARY

The economic-emission load dispatch and short-term hydro-thermal generation scheduling problem considering the environmental aspects have been treated in this chapter. The air pollution and gaseous emissions produced by electric power plants have been attracting more public attention stimulated by the harmful impacts on the atmosphere. Moreover, in order to limit the production of theses emissions, various environmental regulations have recently been issued and applied.

The MBFA has been successfully applied to solve these multi-objective optimization problems. The weighted-sum method has been implemented for each problem to convert the multi-objective problem to a single one. The MBFA has been used to find the optimal solution using various well-known test systems. The algorithm's effectiveness has been shown in each case through obtaining optimal or close to optimal solutions. For the various cases, the MBFA has successfully captured the shape of the Pareto optimal front and the trade-off set of solutions. In each case study, the MBFA has been used to solve bi-objective cases and then the number of objectives has been extended to three and four. An important advantage of the algorithm is its capability to obtain a well-distributed set of solutions on the trade-off curve regardless of the number of objectives.

CHAPTER 7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions and Remarks

The utilization of optimization techniques in the area of power system operation has been one of the important and rapidly developing topics. Powerful optimization techniques have been extensively employed to achieve better performance of electrical power systems with respect to various operational and planning practices. These are not only in terms of operational security and reliability but also in terms of economic and environmental perspectives.

In this thesis, the economic and environmental aspects of power generation systems are discussed and analyzed in order to accomplish the most optimum operational practice. The optimal operation can be defined differently according to various viewpoints. One point of view considers the maximization of profit and minimization of production costs as priority. In contrast, from an environmental perspective, minimizing the harmful impacts of the gaseous emission is an imperative objective. These two conflicting objectives in particular are considered in both the single and multi-objective optimization of power system operation treated in this thesis.

In general, optimization methods are classified into two main categories; deterministic and heuristic. In this thesis, one of the recently introduced heuristic optimization methods, BFA, has been discussed, developed and employed to treat the considered economic and environmental optimization problems of power system operation.

A modified bacterial foraging algorithm (MBFA) has been proposed, developed and validated using a wide range of well-known benchmark optimization functions. These functions are carefully selected to demonstrate the effectiveness of the proposed MBFA. The capability of the MBFA in solving various optimization problems with different characteristics has been proven. Various types of optimization functions were considered including single and multi-objective, constrained and unconstrained functions. Nonlinearity, non-smoothness and non-convexity of the targeted objective functions and constraints were also taken into consideration.

MBFA has been utilized to optimally solve the classical economic dispatch (ED) problem considering various practical operational constraints. In this regard, the ED problem has been solved considering the transmission power losses in some cases and the valve-point effects in others. A wide range of case studies have been selected such that various practical aspects are represented and analyzed.

Unlike the ED, the hydro-thermal generation scheduling problem is a dynamic problem where the power schedule is determined over an operational period of time. In this thesis, the short-term hydro-thermal scheduling (STHTS) problem has been comprehensively discussed and effectively solved using the MBFA. The problem has been analyzed and solved considering various hydraulic configurations in terms of reservoir location arrangement and water availability and capacity. Hydro-electric plants with fixed-head and variable-head reservoirs have been considered. In addition, hydraulically isolated plants on different streams as well as hydraulically coupled on the same stream or cascaded in a multi-chain plant configuration have also been treated. A considerable number of test systems have been successfully solved using the proposed MBFA. These cases have been carefully selected to represent the various practical thermal and hydraulic characteristics and operational constraints of the STHTS optimization problem.

Adding the environmental dimension is also one of the issues considered as part of the scope of this effort. Both the ED and STHTS problems are subsequently formulated as multi-objective optimization functions in order to consider the environmental part of the problem. The two multi-objective optimization problems have been efficiently solved using the proposed algorithm. The MBFA is adapted to capture the Pareto optimal curve of the optimal set of solutions and trade-off relationships of the conflicting objective functions.

The comprehensive literature review contained in this thesis demonstrates the application of optimization methods used to solve various power system optimization problems. The focus of this review is the optimization approaches related to the problems discussed in this thesis. It considers deterministic and heuristic optimization techniques applied for both single and multi-objective optimization problems in power systems.

7.2 Future Work

The areas of the research and the solution methods presented in this thesis can be further explored and extended to wider horizons. The following research points are the most promising topics that could be the subject of extended analysis:

- The problems discussed in this research can be further expanded considering additional constraints. These may include minimum up and down times of generating units, spinning reserve, ramp rates and prohibited zones of operation.
- Renewable energy such as wind and tidal energy can be considered in the optimization problems discussed in this thesis. Investigating the possibility of the wind energy optimization in terms of economic dispatch is an interesting field of research.
- The classic economic-dispatch problem tackled in this work can be reconsidered as a dynamic economic-dispatch one. This is to solve the problem over a specific period of time.
- The problems studied in this thesis can be solved using other heuristic optimization methods that have been introduced recently. Examples of these methods are artificial bee algorithms, shuffled frog-leaping optimization and other heuristic techniques. Results obtained using these methods can be compared with those obtained by the MBFA presented in this thesis.
- The multi-objective power system optimization problems discussed in this thesis can be reconsidered using other aggregation methods such as ε-constraint and other multi-objective solution approaches discussed in Chapter 3. The performance of the MBFA can be compared using these different aggregation methods considering the same problem.
- Incorporating the fuzzy set theory in the field of decision making can be considered in order to decide the best-compromised solution among the non-inferior solutions for the multi-objective optimization problems.
- Statistical generalized models can be implemented in order to tune the algorithm parameters. This could be a promising research especially when errors are not normally distributed.

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APPENDIX

Table A.1 Typical Fossil Generation Unit Net Heat Rates*

		Output (MJ/kW hr)				
Fossil fuel	Unit rating	100%	80%	60%	40%	25%
Coal	50	11.59	11.69	12.05	12.82	14.13
Oil	50	12.12	12.22	12.59	13.41	14.78
Gas	50	12.33	12.43	12.81	13.64	15.03
Coal	200	10.01	10.09	10.41	11.07	12.21
Oil	200	10.43	10.52	10.84	11.54	12.72
Gas	200	10.59	10.68	11.01	11.72	12.91
Coal	400	9.49	9.53	9.75	10.31	11.25
Oil	400	9.91	9.96	10.18	10.77	11.75
Gas	400	10.01	10.06	10.29	10.88	11.88
Coal	600	9.38	9.47	9.77	10.37	11.40
Oil	600	9.80	9.90	10.20	10.84	11.91
Gas	600	9.91	10.01	10.31	10.96	12.04
Coal	800/1200	9.22	9.28	9.54	10.14	-
Oil	800/1201	9.59	9.65	9.92	10.55	-
Gas	800/1202	9.70	9.75	10.03	10.67	-

*For Conversion: 1Btu=1054 J

Table A.2 Typical Fuel Cost Coefficients

	Coal			Oil			Gas		
Unit size (MW)	a_i	b_i	c_i	a_i	b_i	c_i	a_i	b_i	c_i
50	0.0103	10.06	49.92	0.0116	10.47	52.87	0.0117	10.66	53.62
200	0.0023	8.67	173.61	0.00238	9.039	180.68	0.00235	9.19	182.62
400	0.0015	8.14	300.84	0.0015	8.52	312.35	0.0015	8.61	316.45
600	0.00053	8.28	462.28	0.00056	8.65	483.44	0.00059	8.73	490.02
800	0.00099	7.48	751.39	0.00107	7.74	793.22	0.00117	7.73	824.40
1200	0.00067	7.47	1130.80	0.00072	7.72	1194.60	0.00078	7.72	1240.32