ALTERNATIVE METHOD FOR ECONOMIC DISPATCH UTILIZING GREY WOLF OPTIMIZER

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ABSTRACT

Power system is one of the largest and most complex engineering systems created by human. The systems are created in order to ensure the longevity and sustainability of the energy for civilization development. As been known, the non-storage characteristics of electricity and constantly rising prices for labour, supplies and maintenance cost worldwide call for the need of economically power system operation. Economic Dispatch (ED) has the objective of dividing the power demand among the online generators economically while satisfying various constraints. Small improvements in optimal output scheduling can contribute significantly in term of cost savings. Although several optimization methodologies have been developed for solving ED problems, the complexity of the task reveals the necessity for development of efficient algorithms to accurately locate the optimum solution. Thus, the objective of this research is to demonstrate an alternative approach for solving ED problems, aiming to provide a practical alternative for conventional methods. In this research, Grey Wolf Optimizer (GWO) is chosen because it has not been implemented in solving ED problem. Besides, the performance of the algorithm had been benchmarked on 29 well-known test functions and is able to give very competitive results compared to others well-known metaheuristic. In addition, the flexibility of this algorithm is a merit to solve different problems by only setting few parameters such as number of population and number of iteration without any special changes in the structure of the algorithm. Thus, in this research, GWO has been successful to solve higher-order nonlinearities and discontinuities characteristic of ED due to valve-point loading effects, ramp rate limits and prohibited zones. To show the feasibility and applicability of the proposed method, seven different test cases which consist of all types of practical constraints were applied and analyzed and the results were compared with recent research studies. From the simulation results, it shows that GWO is able to find the combination of scheduling generators in order to minimize the fuel cost. It has been observed that the GWO also has the ability to converge to a quality solution and possesses an alternative method for solving ED problems.

ABSTRAK

Sistem kuasa adalah salah satu sistem kejuruteraan terbesar dan paling kompleks yang pernah dicipta oleh manusia. Sistem itu dibuat bagi memastikan kelangsungan dan kemampanan tenaga untuk pembangunan tamadun. Seperti yang telah diketahui, ciri-ciri tenaga elektrik yang tidak boleh disimpan dan peningkatan kos bahan api di seluruh dunia menjadikan perlunya kepada operasi sistem kuasa yang ekonomi. Salah satu isu utama yang masih muncul sebagai masalah asas paling kompleks dalam operasi sistem kuasa adalah Penghantaran Ekonomi (ED). ED mempunyai objektif untuk membahagikan kuasa permintaan antara penjana dalam talian yang ekonomi yang memenuhi pelbagai kekangan. Peningkatan kecil dalam penjadualan keluaran optimum boleh menyumbang dengan ketaranya dari segi penjimatan kos. Walaupun beberapa kaedah pengoptimuman telah dibangunkan untuk menyelesaikan masalah ED, kerumitan tugas pembahagian penjanaan mendedahkan kepada perlunya untuk pembangunan algoritma yang cekap dan tepat dalam penyelesaian optimum. Justeru, objektif penyelidikan ini adalah untuk memperkenalkan pendekatan alternatif untuk menyelesaikan masalah ED, yang bertujuan untuk menyediakan satu alternatif yang praktikal selain kaedah konvensional. Dalam kajian ini, Grey Wolf Optimizer (GWO) dipilih kerana teknik ini belum pernah diaplikasikan dalam menyelesaikan masalah ED. Sehubungan itu, prestasi algoritma ini pernah diuji dengan 29 kes ujian penanda dan terbukti ia memberi pencapaian yang kompetitif berbanding teknik-teknik lain yang popular.Tambahan pula, fleksibiliti algorithma ini adalah satu merit untuk menyeleaikan pelbagai masalah yang berbeza dengan hanya menetapkan parameter seperti nombor populasi dan nombor lelaran tanpa membuat sebarang perubahan pada struktur algoritma tersebut. Dalam penyelidikan ini, GWO berjaya menyelesaikan masalah bukan linear yang berperingkat tinggi dan ciri-ciri ED yang tidak berterusan. Untuk menunjukkan kemungkinan dan kesesuaian kaedah yang dicadangkan itu, sebanyak tujuh kes ujian yang berbeza yang terdiri daripada semua jenis kekangan praktikal digunakan dan dianalisis dan hasilnya dibandingkan dengan kajian penyelidikan yang sedia ada. Hasil daripada simulasi, ia menunjukkan bahawa GWO mampu untuk mencari gabungan penjana penjadualan untuk mengurangkan kos bahan api. Daripada penyelidikan ini juga didapati GWO mempunyai keupayaan untuk bertumpu kepada penyelesaian yang berkualiti dan ia memberikan satu kaedah alternatif untuk menyelesaikan masalah ED.

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$F(P_G)$	Total fuel cost
a_i, b_i, c_i	Cost coefficients of the i^{th} generator
P_G	Vector of real power outputs of generators
P_{Gj}	Output generation of unit j
B_{ij}	ij^{th} element of the loss coefficient square matrix
B_{i0}	i^{th} element of the loss coefficient.
B_{00}	Loss coefficient constant.
P_{Gi}	Output power of generator i
P_{Gi}^{0}	Previous output power.
UR_i	Up ramp limit of the i^{th} generator
DR_i	Down ramp limit of the i^{th} generator
$P_{Gi}^{\min}$	Minimum power output limit of generator i
$P_{Gi}^{\max}$	Maximum power output limit of generator i
$P_{Gi,j}^{lower}$ & P_{Gi,PZ_i}^{upper}	Lower and upper boundaries of prohibited operation zone j
P_D	Power demand
P_{loss}	Power losses
e_i , f_i	Coefficients of i^{th} generator with valve point loading
α	Fittest solution of GWO
β	Second best solution of GWO
δ	Third best solution of GWO

LIST OF SYMBOLS

$\vec{D}$	Position of each hunter
$\vec{X}$	Position vector of grey wolf
X_p	Position of the prey
$\vec{A}$, $\vec{C}$	Coefficient vectors
r_1, r_2	Random vectors [0, 1]
X_1	Best position of α
X_2	Best position of β
X_3	Best position of δ
$X\ (t+1)$	Final position
PF	Penalty factor

LIST OF ABBREVIATIONS

ED	Economic Dispatch
GWO	Grey Wolf Optimizer
EDPQ	Economic Dispatch with Piecewise Quadratic
POZ	Prohibited Operating Zones
SI	Swarm Intelligence
GA	Genetic Algorithm
SA	Simulated Annealing
EP	Evolutionary Programming
ACO	Ant Colony Optimization
TS	Tabu Search
QP	Quadratic Programming
SQP	Sequential Quadratic Programming
DED	Dynamic Economic Dispatch
PSO	Particle Swarm Optimization
ES	Evolution Strategy
ADHDE	Ant Direction Hybrid Differential Evolution
DE	Differential Evolution
NPSO	New Particle Swarm Optimization
ABC	Artificial Bee Colony
ABCNN	ABC with Neural Network
SOH-PSO	Self-Organizing Hierarchical Particle Swarm Optimization

LIST OF ABBREVIATIONS

RCGA	Real Coded Genetic Algorithm
BBO	Biogeography Based Optimization
DE/BBO	Hybrid Differential Evolution with Biogeography Based Optimization
MBFA	Modified Bacterial Foraging Algorithm
FA	Firefly Algorithm
CS	Cuckoo Search Algorithm
NMPSO	New Modified Particle Swarm Optimization
ICA-PSO	Improved Coordinated Aggregation-Based Particle Swarm Optimization
SQP	Sequential Quadratic Programming
PSO-SQP	Particle Swarm Optimization Sequential Quadratic Programming
GAB	Binary Genetic Algorithm
GAF	Floating-point Genetic Algorithm
CEP	Classic Evolutionary Programming
FEP	Fast Evolutionary Programming
MFEP	Mean Evolutionary Programming
IFEP	Improved Fast Evolutionary Programming
PS	Pattern Search
GSA	Gravitational Search Algorithm
HDE	Hybrid Differential Evolution
CGA-MU	Conventional Genetic Algorithm with Multiplier Updating
EP-SQP	Evolutionary Programming Sequential Quadratic Programming

LIST OF ABBREVIATIONS

UHGA	Uniform Hybrid Genetic Algorithm
QPSO	Quantum Particle Swarm Optimization
IGA-MU	Improved Genetic Algorithm with Multiplier Updating
ST-HDE	Self-turning Hybrid Differential Evolution
HGA	Hybrid Genetic Algorithm
HQPSO	Hybrid Quantum PSO
HGPSO	Hybrid Gradient PSO
SPSO	Simple PSO
HGAPSO	Hybrid Genetic Algorithm with PSO
TM	Taguchi Method
MPSO	Modified PSO
ESO	Efficient Evolutionary Strategy Optimization
HPSOM	Hybrid PSO
PSO-LRS	PSO with Local Random Search
IGA	Improved Genetic Algorithm
HPSOWM	Hybrid Particle Swarm Optimization with Wavelet Mutation
DEC-SQP	Chaotic Differential Evolution with Sequential Quadratic Programming
APSO (1)	Anti-predatory Particle Swarm Optimization (without considering global worst position)
APSO (2)	Anti-predatory Particle Swarm Optimization (with considering global worst position)
NPSO-LRS	New Particle Swarm Optimization with Local Random Search

LIST OF ABBREVIATIONS

BF	Bacterial Foraging Algorithm
GA-PS-SQP	Genetic Algorithm Pattern Search Sequential Quadratic Programming
DS	Differential Search
MFA	Modified Firefly Algorithm
PC-PSO	Passive Congregation PSO
LI	Lamda Iteration
HM	Harmony Search
GAMS	General Algebraic Modelling System
PSO-TVAC	PSO with Time Varying Acceleration Coefficients

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CHAPTER 1

INTRODUCTION

1.1 Background

Economic Dispatch (ED) in power system has the objective of generation allocation of the power generators, in such a manner that the cost of generation is minimized while all operating constraints are satisfied. As electric energy cannot be stored, the power generation should be met the variations of loads. It is required to commit enough number of generating units to meet the load demand in real time. In short, the load demands are to be met while operating the power system in the most economic manner. Therefore, ED problem is considered to be one of the fundamental problems in electric power system operation.

Previously, conventional optimization methods assume generator cost curves to be continuous and monotonically increasing, but modern generators have a variety of nonlinearities in their cost curves, making this assumption inaccurate, and resulting approximate dispatches a lot of revenue loss. Thus, ED which combines a highly non-linear and constrained problem is really needed for optimal in order to return a profit on the capital invested.

Optimization played a vital role in engineering and sciences field. This nonlinear constrained optimization problem has been resolved by various types of optimization techniques. Most conventional or classic algorithms are deterministic. For example, the simple method in linear programming is deterministic (Xin-she Yang, 2010). Many of them are gradient-based which depend on gradient information such as well-known Newton-Raphson algorithm. Since it uses the function values and their derivatives thus it works extremely well for smooth unimodal problems. Nevertheless, if there is some discontinuity in the objective function, it does not go well.

For stochastic algorithms, in general, there are two types of stochastic algorithm: heuristic and metaheuristic though their difference is minor. Generally, heuristic optimization gives quality solutions to a tough optimization problem and can be found in a reasonable amount of time, but there is no guarantee that optimal results are achieved (Xin-she Yang, 2010). Further development over the heuristic algorithms is the so-called meta-heuristic algorithms. Here, the meta- means 'beyond' or 'higher level', and they generally perform better than simple heuristics (Xin-she Yang, 2010). Recently, researchers tend to name the entire stochastic algorithm with local search and randomization as metaheuristic. Grey Wolf Optimizer (GWO) is one of the most developed and important paradigm of the meta-heuristic computation (Mirjalili and Lewis, 2014a). This thesis investigates the application of the GWO independently for the solution of the economic dispatch problem. GWO was expected to give the optimal result for ED in this research compared to recent literature reviews.

1.2 Problem Statement

Traditionally, in the ED computation, the cost function for each generator is represented by a quadratic function which is convex in nature, as well as increasing monotonically with linear constraints. Linear constraints can be listed down as follows (M. Vanitha, 2012):

i. Generation capacity constraints
ii. Power balance constraint

The actual characteristics of generators are drawn by considering the inequality constraints and ramp rate limit. Ramp rate or power response rate is described as the power response capability of the unit in terms of accommodating power changes in specified time interval. The operating range of all on-line units is restricted by their ramp rate limits. These characteristics exhibit higher order non-linearity and discontinuities.

Nowadays, a non-convexity appears in the characteristic curves. The major non-convex economic dispatch problems can be listed as follows (Malik, 2009):

i. Economic dispatch with piecewise quadratic cost function (EDPQ)
    - Piecewise quadratic cost function due to the valve point effect
    - Piecewise quadratic cost function due to the multiple fuel mix

ii. Economic dispatch with Prohibited Operating Zones (POZ).

One way to solve the ED problems with quadratic cost functions is by gradient-based optimization methods. For example, Newton-type methods which are only suitable for the fuel-cost curve with linear and monotonically increasing functions. However, ED problems with multiple-unit and piecewise quadratic cost functions will occur many local extreme points and resulting in huge revenue losses over the time.

As a result, conventional optimization techniques are no longer the finest choice since they may fail to locate the optimal solution and result in considerable errors. Thus, the non-convex nature of the ED problem requires accurate, robust and fast solution optimization techniques to avoid getting stuck in local optima. In this respect, stochastic search algorithms like Genetic Algorithm (GA), Evolutionary Search (ES), Particle Swarm Optimization (PSO) and etc. may prove to be very efficient in solving highly non-linear ED problem without any restrictions on the shape of cost curves.

Although these metaheuristic methods do not always guarantee the global optimal solution, they generally provide a reasonable solution (sub-optimal or near global optimal). These bring the motivation to solve highly non-linear ED problems by applying the stochastic search algorithms, GWO.

1.3 Objectives

The primary objective of this research is to incorporate the alternative meta-heuristic technique, namely Grey Wolf Optimizer (GWO) in solving the practical

Economic Dispatch (ED) problems. In order to achieve the main objective, the research is divided into the following sub-objectives, as follows:

i To minimize the generation cost of thermal power plants while satisfying the load demand with consideration of practical operation constraints of generating units.

ii To validate the capability of GWO in solving ED problems by using MATLAB software.

1.4 Scope of the Research

The scope of research can be broken down as below:

i Several problems of thermal power generations such as the piecewise quadratic cost function, generations levels between the minimum and maximum limits, power balance constraints, ramp rate limits, Prohibited Operating Zones (POZ) and the valve point loading effects are covered in order to test the feasibility of GWO.

ii The effectiveness of the proposed GWO will be validated using MATLAB.

iii There are seven test cases been decided which are 3, 6, 13, 15, 20, 38 and 40-unit generating systems with a power demand of 850 MW, 1263 MW, 1800 MW, 2630 MW, 2500 MW, 6000 MW and 10500 MW respectively. The constraints of generation capacity, power balance with transmission loss, ramp rate limits and prohibited operating zones are considered for a 6-unit and a 15-unit system. The 20-unit system is used with the generation capacity constraint and power balance constraint with transmission loss. 38-unit system is used with the generation capacity constraint and power balance constraint without transmission loss. The valve point loading effects, generation capacity constraint and power balance constraint without transmission loss are considered for a 3, 13 and 40-unit system.

1.5 Thesis Organization

Chapter 2 presents the Literature review about the techniques that have been applied in solving Economic Dispatch (ED) problems. The related issues regarding ED also have been reviewed extensively in this chapter.

Chapter 3 will explain about the implementation of GWO to solve the ED problems. The mathematical formulations of economic dispatch problem and mathematical model of GWO are reviewed briefly in this chapter. Chapter 4 will analyzed and discussed the results of implementation of GWO on ED which tested on various test cases.

Finally, Chapter 5 will draw conclusion of the research work on GWO technique to solve the ED problems along with the contributions of this research and the suggestions for the future scope of the present research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The engineers have been very successful in increasing the efficiency of boilers, turbines and generators so continuously that each new added to the generating unit plants of a system operates more efficiently than any older unit on the system. By operating the system for any load condition, the contribution from each plant and from each unit within a plant must be determined so that the cost of the delivered power is a minimum.

Majority of generating systems is of three types: nuclear, hydro, and thermal (using fossil fuels such as coal, oil and gas). Nuclear plants tend to be operated at constant output power levels. The operating cost of hydro units does not change much with the output. The operating cost of thermal plants, however, changes significantly with the output power level. Thus, in this chapter, the problem of ED for power systems consisting of thermal units only as generators will be discussed.

2.2 Electrical Power System

Power system is the largest man-made complex system. It basically consists of generating sources, transmission network and distribution centres. Secure and economic operation of this system is a challenging task. The primary concern of electric power system operation is to guarantee adequate optimal generation to meet the load demand by satisfying the numerous constraints enforced from different directions (Jasmin and P, 2008).

In a regulated monopoly, an electric power system can be divided into four main functional zones; generation, transmission, distribution and retail service (Malik, 2009).

a) Generation – generation is the conversion of electric energy from other forms of energy like chemical (gas, coal, and hydrogen), nuclear, solar, hydro energy, geothermal energy, wind and wave energy.
b) Transmission – transmission is the transfer of bulk electric energy from one place to another through some transmission network. It connects the generator network and distribution network.
c) Distribution – distribution is the process of delivering electric power from the local network to the consumers.
d) Retail Service – retail service can broadly called retail customer service. Its main function is measuring and billing customers for the power delivered.

In the early days, electrical power system was developed on the concept of natural monopoly. Later it was realized that the electric power industry was not necessarily a natural monopoly at least when it came to generating electricity. It was proven that open access and competition in business lowers the unit price. The same is believed to happen in electric power industry. The competition will encourage new technologies for generating electricity with better efficiency and inefficient generating plants will die out. Same goes with economic dispatch problems, the researchers keep on proposing new optimization techniques to optimize the ED problem in order to reduce the operation cost of generations.

2.3 Economic Dispatch of Thermal Units

EPAct defines "Economic Dispatch" by means of, "*The operation of generation facilities to produce energy at the lowest cost to reliably serve consumers, recognizing any operational limits of generation and transmission facilities.*" [EPAct2005, Sec.1234 (b)]. The demand of the power keeps increasing and the energy cost swings over the years.

Economic Dispatch (ED) is the on-line dispatch, which is used for the distribution of load among the generating units. It is actually paralleled with the system in such a manner that the total fuel cost of the thermal generation is minimized. Historically, economic dispatch has been carried out since 1920. It was the time when engineers were concerned with the problem of economic allocation of generation or the proper division of the load among the generating units available.

Prior to 1930, the methods in use include: the base load method and best point loading. It was recognized as early as 1930, that the incremental method, later known as the equal incremental method, yielded the most economic results. The analog computer was developed to solve the coordination equations. A transmission loss penalty factor computer was developed in 1954. An electronic differential analyzer was developed and used in ED for both offline and on-line since 1955. The digital computer was investigated in 1954 for ED and is being used to date (Malik, 2009).

ED problem is the real solution of a large number of load flow problems and the optimum solution is the one that needs minimum cost for generation. In addition, ED is an important optimization task in power system operation for allocating generation among the committed units such that, the constraints imposed are satisfied and the energy requirements in terms of British thermal units per hour (Btu/h) or dollar per hour ($/h) are minimized. In fact, the modern power system has to be operated under various operational and network constraints.

Therefore, researchers still keep looking for the best solution to minimize the operation costs of power generations. Generators must be operate efficiently and economically. The objective of solving the ED problem is scheduling the generators' output so the total cost is minimized while sustaining the power demand and other constraints.

2.4 Literature Review

Many traditional optimization techniques were discussed by Wood (Wood and Wollenberg, 1996) to optimize the ED problem. They are Lambda iteration, Gradient search, Newton method, Dynamic programming and Base point and participation factors. However, these methods assume the generator cost functions as linear and as increasing monotonically. Practically, the actual cost functions of the practical systems are nonlinear. Such approximations seem to be impractical and may lead to a sub-optimal solution.

Since the ED problem turns out to be a complex non-convex optimization problem, many non-traditional optimization algorithms have been developed to solve the ED problem in the past decades and have been described in the previous literature. Few such heuristic optimization techniques developed by the researchers to solve the ED problem are explained below with the constraints used.

Chen and Chang, (1995) solved the ED problem for the large scale system using Genetic Algorithm (GA). The constraints considered are the ramp rate limits and prohibited operating zones. The transmission loss is also taken into account. This method is implemented for a 3-unit system with 300 MW demand and a 40-unit system with a demand of 10500 MW. This method is attractive in large-scale problems. This approach can also take network losses, ramp rate limits, and prohibited zone avoidance into account to make the dispatch more practical. Evaluation results based on the Taipower system show that the approach is faster than the well-known lambda-iteration method in large-scale systems.

In the same year, Po Wong, (1995) proposed a constrained Simulated Annealing (SA) approach to solve the ED problem with a power balance and inequality constraint. This approach is based on the process of crystallization of molten metal through the process of slow cooling. The algorithm is tested for a 3-unit system with a demand of 850 MW. The advantage of this method is that it does not depend on the initial solution. In solving the economic dispatch problem, the new method does not require the evaluation of incremental fuel costs, and hence it can deal with highly non-linear input-output characteristics of thermal generators. Another advantage of the method is that its performance is not sensitive to the initial dispatch solution. However, its convergence to an optimal solution is very slow.

Orero and Irving, (1996) used the GA for ED problem in two different methods, one is the Standard GA and the other is the Deterministic Crowding GA in which the diversity of the populations is maintained by creating a new population, wherein the parent is replaced by the child when it has got most similar values and it requires only a few parameters. The methods are applied to 15-unit system for a demand of 2650 MW with prohibited operating zones. The use of a parallel local hill climbing algorithm on the final population of the crowding algorithm can produce better solutions in reduced computation times.

Hong-Tzer Yang, Pai-Chuan Yang and Ching-Lien Huang, (1996) implemented an Evolutionary Programming (EP) technique to solve a highly non-linear and discontinuous ED problem. Three cases were considered; 3-unit system with a demand of 850 MW and without valve point loading effects, 3-unit system of 850 MW load with valve point loading effects and a 40-unit system of variable demand for 24 hours with valve point loading effects. In this approach, most of the solution would avoid entrapped in the local optima. According to Yang, EP is better than GA in searching for a global optimum but not in CPU execution time.

Su and Chiou, (1997) described the direct computation Hopfield method for solving an ED problem. This method uses a linear input-output model for neurons and the weighting factors are calculated. This method has been applied to systems consisting only of linear constraints such as 3-unit and 13-unit system having a demand of 850MW and 2520MW respectively.The proposed method is very easy to apply due to the determination of the weighting factors of the energy function is unnecessary. Furthermore, the proposed model, unlike other neural networks, requires no training.

Song, Chou, and Min, (1999) applied an Artificial Ant Colony Search Algorithm (ACSA) to an ED problem. This is a new cooperative agent search approach obtained from the food foraging behavior of ants. This approach is validated through 40-unit system. The results obtained clearly show the ACSA converges to the optimum solution through an auto catalytic process. The massive parallel agent cooperation makes the ants able to jump over the local optimum and to identify the right cluster easily; hence, a good solution can be found. Although the results of this paper is very encouraging, there is a common problem always faced by bio-inspired algorithm which is particularly in the areas of improvement of its computation efficiency.

Su and Lin, (2000) developed a Hopfield Model based approach for solving the ED problem with the power balance constraint including transmission loss and the generation capacity constraint. To test the efficiency of the approach, it is tested on 3-unit system with a demand of 210MW and 20-unit system of demand 2500MW. Computational results reveal that the proposed method is superior to the conventional lambda-iteration method in computational requirement.

Lin, Cheng, and Tsay, (2001) suggested a new optimization technique in which EP, Tabu Search (TS) and Quadratic Programming (QP) was integrated and is applied to a non-convex ED problem. Hybrid EP and TS was used for quality control and the QP for performance enhancement. The method was tested on two test systems such as 10-unit system with a demand of 2400MW, considering only linear constraints and 15-unit system with a demand of 2650MW with prohibited operating zones.This optimization technique is better than GA in aspect of quality and performance due to its active repairing strategy to probe for the new solution while GA uses penalty function to passively test feasible and infeasible solutions.

Attaviriyanupap and Kita, (2002) proposed a hybrid optimization technique where in the EP and Sequential Quadratic Programming (SQP) are hybridized. It is used to solve the Dynamic Economic Dispatch (DED) with non-smooth cost function. The EP is used to perform a base level search and leads to global search region and the SQP is used to conduct a local search in that region to find the optimal solution. The hybrid method is employed for 10 unit 24 hour system with ramp rate limits to evaluate its performance. Simulation results demonstrate that the proposed method can give a cheaper total production cost than those obtained from EP or SQP alone.

Gaing, (2003) described Particle Swarm Optimization (PSO) method for an ED problem with non-linear characteristics. It is a population-based technique motivated by the biological concepts like swarming and flocking. The generator constraints such as ramp rate limits and prohibited operating zones are considered with network loss. This method is tested on 6-unit system with 1263MW demand, 15-unit with 2630MW demand and 40-unit system with 8550MW demand. The advantage of this method is its fast convergence. The results show that the proposed method was indeed capable of obtaining higher quality solution efficiently in ED problems.

Park and Lee, (2005) developed a new approach using modified PSO (MPSO). It is applied to an ED problem with non-smooth cost functions. A position adjustment strategy is incorporated in the PSO framework in order to provide the solutions satisfying the inequality constraints. This modified PSO is considered with valve point loading effects and multi-fuel options.Two cases are taken for implementation, namely, 3-unit system with 850MW load and 40-unit system with 10500MW load. In the case of nonsmooth function problem due to multi-fuel effects, the MPSO has shown superiority to the conventional numerical method, the conventional Hopfield neural network, and the evolutionary programming approach, while providing very similar results with the modified Hopfield neural networks.

Pereira-Neto, Unsihuay, and Saavedra, (2005) adopted a novel optimization technique using Evolution Strategy (ES) for non-convex ED problem. Two operations recombination and mutation are involved in ES to generate a new solution and to improve the local search. In addition to valve point loading effects, ramp rate limits and prohibited zones, generator constraints are also involved. The method is tested on 3-unit with 850MW load, 13-unit with 2520MW load, 15-unit with 2650MW load, 6-unit with 1263MW load and a 40-unit with 10500MW load system.

Mahadevan, Kannan, and Kannan, (2005) used PSO to solve the ED problem with linear constraints, valve point effects and ramp rate limits. The effect of prohibited zones is neglected. This method is applied on a 6 unit system to test its performance. The PSO algorithm approach yields solutions which are optimal or near optimal. The results obtained for the IEEE 30-bus 6-unit test system showed that the PSO algorithm was good in terms of its potential in solving ED problems and also computational time besides the high quality of solutions compared to the evolutionary programming (EP) method.

Wang, Liu, and Chiou, (2006) applied an Ant Direction Hybrid Differential Evolution (ADHDE) to solve the ED problem in a power system, where the Ant Colony search technique is employed to determine the correct mutation operation for hybrid DE to generate a global optimum solution. 6-unit system having a demand of 1263 MW is considered with transmission loss and prohibited operating zones. 15-unit system with a demand of 2650 MW and prohibited zones is also chosen. ADHDE is quite fast for finding the global solution compared to GA and SA.

Panigrahi, (2006) discussed the SA technique for solving Dynamic Economic Dispatch (DED) problem by considering the power balance constraint with transmission losses, operating limits, valve point loadings and ramp rate constraints, in order to determine the global or near global optimum solution. The main drawbacks of this proposed algorithm is that the computing time requirement is high.

Coelho and Mariani, (2006) developed an algorithm by combining a chaotic Differential Evolution (DE) and Quadratic Programming (QP). This algorithm is applied to an ED problem with valve point loading effects. In this, DE with chaos sequences is the global optimizer and the QP is the local optimizer. To evaluate the performance, it is tested on 13-unit and 40-unit system with 1800 MW and 10500 MW respectively. This method which combining DE, chaos sequences, and SQP can be very effective in solving ED problems with the valve point effect.

Aristidis, (2006) described a successful use of Ant Colony Optimization (ACO) algorithm in the implementation of ED problem with linear constraints, neglecting the transmission network loss. In the actual ant system, an exclusive strategy is introduced after each iteration to give importance to the best path obtained so far. 6-unit generator system is used to validate the performance of the approach. The mentioned algorithm yields solution values that are comparable to those of GA, PSO algorithms and Gradient-Based approach.

Chiang, (2007) suggested an improved GA with multiplier updating (IGAMU) for solving the ED problem. It improves the evolutionary direction and migrating operator for the efficient and active search. Multiplier updating is used to avoid the deforming of the augmented Lagrange function. This method is implemented on 13-unit system of 2520 MW load with valve point loading effects and 15-unit system having 2650 MW load with prohibited operating zones. The proposed algorithm integrates the IGA and the MU such that it has the following merits: straightforward concept; easy implementation; better effectiveness than previous methods. Comparative results demonstrate that the proposed algorithm has these merits mentioned earlier in real-world ED operations.

Selvakumar and Thanushkodi, (2007) proposed a New PSO (NPSO) to optimize anon-convex ED problem. A modification is done in the cognitive behavior of the particle in order to remember the best and worst previous visited positions. To pave a way in developing a good solution region, a simple local random search procedure is included in NPSO (NPSO-LRS). This procedure is validated through three test cases like 6-unit system with the ramp rate limits, prohibited zones and a demand of 1263 MW, 40-unit system with valve point loading effects and a demand of 10500 MW, 10-unit system with multi-fuel options and valve point loading effects and a demand of 2700 MW. It is proved that the proposed NPSO-LRS method is very effective in giving quality solutions consistently compared to NPSO for nonconvex ED problems.

S. Wang, Chiou, and Liu, (2007) described a self-tuning hybrid DE algorithm to solve the non-convex ED problem in which the 1/5 success rule of evolution strategies is used to improve the search towards global optimum. The ramp rate limits, valve point loadings and prohibited zones are used along with the linear constraints. It is applied on 3-unit system having a demand of 850 MW, 13-unit system with 1800 MW and 40-unit system with 10500 MW load.Three stochastic optimization algorithms, including GA, DE and HDE, are also employed to solve the ED problem for comparison with the self-tuning HDE. The results show that the proposed self-tuning HDE algorithm is superior to the other three (GA, DE and HDE) algorithms in terms of computed minimum fuel cost and computational complexity.

Manoharan and Kannan, (2008) applied a new technique to solve an ED problem known as penalty parameter-less constraint handling scheme. The ideas of evolutionary algorithms such as the real coded GA, PSO and DE were used. The method is implemented by considering the multi-fuel options and valve point loading effects testing on 10 -unit system with variable demand. Simulation results reveal that the PSO approach can give an optimal generation cost more consistently than any other algorithms considered. Among the EAs, DE performed better with respect to the computation time. Nelder–Mead simplex method gives an optimal solution within minimum time compared with all EAs.

Balamurugan and Subramanian, (2008) proposed DE algorithm to solve the Dynamic Economic Dispatch (DED) problem by considering the linear constraints, valve point loading effects and the ramp rate limits except the prohibited operating zones. This algorithm is also a population-based algorithm. It creates a new individual by combining the existing one and keeping the individual having best fitness. Both 5 and 10-unit systems are tested using this algorithm to get the optimal solution. The results show the capability of the algorithm to determine the global or near-global solution for the DED problem.

Hemamalini and Simon, (2011) adopted Artificial Bee Colony (ABC) algorithm, which was employed for an ED problem with a valve point loading effects. This is based on the food searching behavior of honey bees. To test the effectiveness of this approach, 3-unit and 40-unit system were considered for 850 MW and 10500 MW respectively. From the results obtained, it can be concluded that the method is simple and easy to implement, and the convergence rate is fast, the computational time is less, and it is applicable for any large scale system.

B. Panigrahi, Pandi, and Das, (2008) solved the ED problem using Adaptive variable population PSO (APSO) approach by considering the linear constraints with transmission loss, ramp rate limits and prohibited zones and also multiple fuels. It is tested on different units to prove its proficiency. From this limited comparative study, it can be concluded that the APSO can be effectively used to solve smooth as well as non-smooth constrained ED problems.

Chaturvedi, (2008) suggested a technique called Self-Organizing Hierarchical Particle Swarm Optimization (SOH-PSO) to avoid premature convergence in PSO. The

ED problem is considered with both linear and non-linear constraints and tested on 6-unit system with a demand of 1263 MW, 15-unit system with 2630 MW demand and 40-unit system with a demand of 10500 MW. The test results clearly demonstrated that SOH_PSO which is capable of achieving global solutions is simple, computationally efficient and has better and stable dynamic convergence characteristics.

Kuo, (2008) proposed a new Modified Particle Swarm Optimization approach (New MPSO) to improve the searching and the quality of solution of the ED problem. The PSO and SA approaches are hybridized and tested on 6, 13, 15 and 40-unit systems with a demand of 1263 MW, 2520 MW, 2630 MW and 8550 MW respectively.

Vlachogiannis and Lee, (2009) implemented Improved Coordinated Aggregation-Based PSO (ICA-PSO). The linear constraints, the valve point loading effects and the ramp rate limits are considered with the ED problem.With the accuracy of two digit points, the particles search the decision space, thereby improving the convergence. To evaluate the performance of the approach 6, 13, 15 and 40 unit systems are considered with a demand of 283.4 MW,1800 MW, 2650 MW and 10500 MW respectively.

Khamsawang and Jiriwibhakorn, (2009) proposed a global optimization technique known as DE algorithm to solve the ED problem, where the regenerating population procedure is added to the conventional DE to improve the quality of solution and to escape from local minima. It is applied on 3-unit system with valve point loading effects. The total demand of the given system is 850 MW. This method can produce the global optimum solution with minimum convergence time.

Amjady and Nasiri-Rad, (2009) developed an optimization technique called Real Coded GA (RCGA) for solving the ED problem. In addition to linear, the non-linear constraints are also considered. Besides the non-linear constraints such as the ramp rate limits, prohibited zones, valve point loadings, multi-fuel options and spinning reserve constraints, a security constraint is also included. This method is tested on 3-unit, 6-unit, 10-unit and 40-unit system. RCGA with Arithmetic-Average-Bound

Crossover (AABX) and Wavelet Mutation (WM) required less computation time less population size and generation number than the conventional RCGA.

Bhattacharya and Chattopadhyay, (2010) solved the ED problem using the Biogeography Based Optimization (BBO) approach. Biogeography is based on the geographical distribution of species. BBO is based on the two concepts of migration and mutation. All the linear and non-linear constraints are considered. 6, 10, 20 and 40-unit system with a demand of 1263 MW, 2700 MW, 2500 MW and 10500 MW respectively are taken into account to prove the efficiency of the method. It has a good convergence property and can avoid premature convergence.

Bhattacharya and Chattopadhyay, (2010b) also developed a hybrid DE/BBO algorithm for solving an ED problem with all the linear and non-linear constraints. The searching ability of DE is improved by the BBO. To evaluate the performance of the algorithm, four test cases such as 3, 10, 38 and 40-unit systems were used with a demand of 300 MW, 2700 MW, 6000 MW and 10500 MW respectively. It has been observed that the DE/BBO has the ability to converge to a better quality solution and possesses better convergence characteristics and robustness than ordinary BBO.

Meng and Wang, (2010) proposed a new technique to solve the ED problem with valve point loading effects termed as quantum inspired PSO, in which the quantum computing theory is used in addition to self-adaptive probability selection and chaotic sequences mutation to improve the searching ability. The performance of the algorithm is tested by implementing on test systems such as 3-unit system with 850 MW demand, 13-unit system with 1800 MW demand and 40-unit system with 10500 MW. The simulation results show that the QPSO is better than other versions of PSO in terms of the speed and accuracy. Compared to the classical PSO, it greatly enhances the searching ability and efficiently manages the system constraints.

Noman and Iba, (2011) used a new method for solving the Dynamic Economic Dispatch (DED) problem using cellular differential evolution (CDE). To test the performance of the algorithm, two cases have been taken, namely, 10-unit system having 24 dispatch intervals with valve point loading effects and 13-unit system having

24 dispatch intervals with valve point loading effects. The proposed CDE algorithm found new best results in both case studies. This method is well known for preserving the population diversity and thereby reducing the risk of premature convergence.

Nournjad and Kazemzadeh, (2011) described Modified Bacterial Foraging Algorithm (MBFA) to solve the ED problem with linear constraints and valve point loading effects. Five example systems have been used to prove the efficiency of the algorithm. They are 3-unit system with valve point effects and with demand of 850 MW, a 6-unit system with transmission loss and with demand of 1263 MW, 26-unit system with prohibited operating zones and a demand of 2500 MW and finally, a 15 unit system with transmission loss and a demand of 2630 MW. The main advantages of this method are simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques.

From the extensive literature review, it can be concluded that there are various number studies describe various optimization techniques to solve an ED problem with linear and non-linear constraints. Most of the used optimization techniques consist of four main characteristics which are simple implementation, fast convergence, high quality solutions and local optimal avoidance. Hence, with respect to the mentioned characteristics, it is decided to apply new recent metaheuristic optimization techniques, GWO for solving the ED problem considering all the linear (generator capacity and power balance) and non-linear constraints (generator ramp rate limits, valve point loading effects and prohibited operating zones) to obtain minimum total generation cost.

On the other hand, based on the reviews, it has been decided to have seven test cases as, 3-unit, 6-unit, 13-unit, 15-unit, 20-unit, 38-unit and 40-unit generating systems with a power demand of 850 MW, 1263 MW, 1800 MW, 2630 MW, 2500 MW, 6000 MW and 10500 MW respectively to validate the feasibility of GWO in solving highly nonlinear and constraints ED problem. All the test cases have an objective of minimizing F_T, given by equations (3.1) and (3.2). The constraints of generation capacity, power balance with transmission loss, ramp rate limits and prohibited operating zones that are from equations (3.3) to (3.7) are considered for 6-unit and 15-

unit system. The 20-unit system is used with the generation capacity constraint and power balance constraint with transmission loss that is from the equations (3.3), (3.8) and (3.9). 38-unit system is used with the generation capacity constraint and power balance constraint without transmission loss that is from the equations (3.8) and (3.9). The valve point loading effects, generation capacity constraint and power balance constraint without transmission loss that is from the equations (3.8) to (3.10) are considered for 3-unit, 13-unit and 40-unit system.

2.5 Metaheuristic Optimization Techniques

Metaheuristic optimization techniques have become very popular over the last two decades. Surprisingly, some of them such as Genetic Algorithm (GA) (Bonabeau, Dorigo, and Theraulaz, 1999), Ant Colony Optimization (ACO) (Dorigo, Birattari, and Stutzle, 2006) and Particle Swarm Optimization (PSO) (Poli, Kennedy, and Blackwell, 2007) are fairly well-known among not only computer scientists but also scientists from different field. Many important discoveries were done by 'thinking outside the box', and often by accident; that is heuristics. In fact, our daily learning experience (at least as a child) is dominantly heuristic. Undeniably, metaheuristics as a scientific method to problem solving is indeed a modern phenomenon.

Metaheuristics have become remarkably common because of its four main characteristics: simplicity, flexibility, derivation-free mechanism, and local optima avoidance. Firstly, it is simple because the inspiration always comes from the simple behaviour of animals, microorganisms or evolutionary concepts (Mirjalili and Lewis, 2014b). This simplicity of metaheuristic leads computer science to simulate different natural concepts, proposed new metaheuristic and hybridize easily. The simplicity of this kind of optimization assists other scientists to learn metaheuristics quickly and apply them to their problems without taking a lot of time to learn this optimization.

Secondly, flexibility refers to the applicability of metaheuristics to different problems without any special changes in the structure of the algorithm (Mirjalili and Lewis 2014b). Metaheuristics are readily applicable to different problems since they mostly assume problems as black boxes. In other words, only the input(s) and output(s) of a system are important for a metaheuristic. So, all designers need to know is how to represent his/her problem for metaheuristics.

Third, the majority of metaheuristics have derivation-free mechanisms. In contrast to gradient-based optimization approaches such as Newton-Raphson algorithm, meta-heuristics optimize problems stochastically. The optimization process starts with the certain tradeoff of randomization and local search, and there is no need to calculate the derivative of search spaces to find the optimum. This makes metaheuristics highly suitable for real problems in global optimization with expensive or unknown derivative information.

Finally, metaheuristics have great abilities to avoid local optima compared to conventional optimization techniques. This is due to the stochastic nature of meta-heuristics which allow them to ‘think out of box’ to avoid stagnation in local solutions and search the entire search space extensively. The search space of real problems is usually unknown and very complex with a massive number of local optima, thus via the randomization of metaheuristic the solutions can be avoided being trapped at local optima and, at the same time, increases the diversity of the solutions. Therefore, modern metaheuristic algorithms have been developed with an aim to carry out global search with three main purposes: solving problems faster, solving large problems and obtaining robust algorithms (Talbi, 2009).

Many new metaheuristic algorithms have been developed. One major improvement is the Firefly Algorithm (FA) which was based on the flashing characteristics of tropical fireflies by Yang in 2012 (XS Yang, Hosseini and Gandomi, 2012). The attraction behaviour, light intensity coding, and distance dependence provides a surprising capability to enable firefly algorithm to handle nonlinear, multimodal optimization problems efficiently. Furthermore, Cuckoo Search Algorithm (CSA) was based on the brooding behaviour of some cuckoo species (Xin-she Yang, 2014) which was combined with L ́evy flights. The CSA is efficient because it has very good convergence behaviour that can be proved using Markovian probability theory. Other methods such as eagle strategy are also very effective (Xin-she Yang, Deb, and Behaviour, 2009)

Next, the latest developments in metaheuristic algorithm which is the proposed method, Grey Wolf Optimizer (Mirjalili and Lewis, 2014a) be reviewed in order to investigate the feasibility of GWO in solving ED problems.

2.5.1 Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) proposed by S. Mirjalili (2014) is a new metaheuristic algorithm inspired by grey wolves which been chosen for solving ED problem in this research. Grey wolves (Canis lupus) are considered as predators which located at the top of the food chain. They live in group approximately 5 to 12 on average. The particular interest is the grey wolf has a very strict social dominant hierarchy as shown in Figure 2.1.

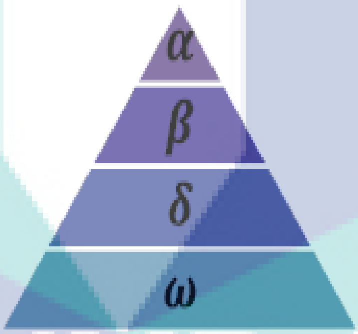

Figure 2.1: Hierarchy of Grey Wolf (dominance decreases from top)

The leader can be a male or a female, called alpha, α . The alpha's decisions are dictated to the pack. However, some kind of democratic behavior has also been observed which means the alpha is not necessarily the strongest but the best in term of managing the pack. Hence, it shows that the discipline of the pack is much more important than its strength.

The second level in the hierarchy of grey wolf is beta, β . He or she probably is the best heir to be the alpha in case one of the alpha wolves passes away or becomes very old. The beta wolf plays the role of an advisor to the alpha and discipliner for the pack. The beta strengthens the alpha's commands throughout the pack and gives feedback to the alpha.

The third level is delta, δ. Delta wolves have to submit to alphas and betas, but they dominate the omega, ω. Scouts, sentinels, elders, hunters, and caretakers belong to this category. Scouts are responsible for watching the boundaries of the territory and warning the pack in case of any danger. Sentinels protect and guarantee the safety of the pack. Elders are the experienced wolves who used to be alpha or beta. Hunters help the alphas and betas when hunting prey and providing food for the pack. Lastly, the caretakers are responsible for caring for the weak, ill, and wounded wolves in the pack.

The lowest ranking grey wolf is omega, ω. The omega plays the role of scapegoat. They are the last wolves that are allowed to eat. It may seem the omega is not an important individual in the pack, but it help to maintain the dominance structure of the entire pack. In some cases, the omega is also the babysitters in the pack.

Group hunting is another interesting social behavior of grey wolves. According to Muro, Escobedo, Spector, and Coppinger, (2011) the main phases of grey wolf hunting are as follows:

- Tracking, chasing, and approaching the prey.
- Pursuing, encircling, and harassing the prey until it stops moving.
- Attack towards the prey

This hunting techniques and the social hierarchy of grey wolves are mathematically modelled in order to design GWO.

2.6 Conclusion

In conclusion, seven test cases with different pratical constraints have been decided to validate the feasibility of GWO in solving highly nonlinear and constraints ED problem. Based on the reviews, the advances in computation found a better solution of complex problems have led to using stochastic optimization techniques for solving ED problems. One of them is population-based metaheuristics. One of the interesting branches of the population-based metaheuristics is Swarm Intelligence (SI). GWO is considered as population-based Swarm Intelligence. The concepts of SI was first proposed in 1993 (Beni and Wang, 1993). According to Bonabeau, Dorigo and Theraulaz (1999), SI is ‘‘The emergent collective intelligence of groups of simple agents’’. The inspirations of SI techniques originate mostly from natural colonies, flock, herds, and schools. There are several popular SI techniques which are ACO (Dorigo, Birattari and Stutzle, 2006) PSO (Kennedy J and Eberhart R., 1995) and Artificial Bee Colony (ABC) (Karaboga and Basturk, 2008). Some of the advantages of SI algorithms are:

- SI algorithms preserve information about the search space over the course of iteration, whereas Evolutionary Algorithms (EA) discard the information of the previous generations.
- SI algorithms often utilize memory to save the best solution obtained so far.
- SI algorithms usually have fewer parameters to adjust.
- SI algorithms have less operators compared to evolutionary approaches (crossover, mutation, elitism, and so on).
- SI algorithms are easy to implement.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The operation of a modern power system has become very complex. It is necessary to maintain frequency and voltage within limits in addition to ensuring reliability of power supply and for maintaining the frequency and voltage within limits it is essential to match the generation of active and reactive power with the load demand. For ensuring reliability of power system it is necessary to put additional generation capacity into the system in the event of outage of generating equipment at some station. Over and above it is also necessary to ensure the cost of electric supply to the minimum. The total interconnected network is controlled by the load dispatch centre. The load dispatch centre allocates the MW generation to each grid depending upon the prevailing MW demand in that area. Each load dispatch centre controls load and frequency of its own by matching generation in various generating stations with total required MW demand plus MW losses. Therefore, the task of load control centre is to keep the exchange of power between various zones and system frequency at desired values.

3.2 Necessity of generation scheduling

In a practical power system, the power plants are not located at the same distance from the centre of loads and there fuel costs are different. Also under normal operating, the generation capacity is more than the total load demand and losses. Thus, there are many options for scheduling generation. In an interconnected power system, the objective is to find the real and reactive power scheduling of each power plant in such a way so as to minimize the operating cost. This means that the generators real and reactive powers are allowed to vary within certain limits so as to meet a particular load demand with minimum fuel cost. This is called the “Economic Dispatch” (ED) problem.

The objective functions, also known as cost functions may present economic cost system security or other objectives. The transmission loss formula can be derived and the economic dispatch of generation based on the loss formula can also be obtained. The Loss coefficients are known as *B*-coefficients.

A major challenge for all power utilities is not only to satisfy the consumer demand for power, but to do so at minimal cost. Any given power system can be comprised of multiple generating stations having number of generators and the cost of operating these generators does not usually correlate proportionally with their outputs; therefore the challenge for power utilities is to try to balance the total load among generators that are running as efficiently as possible.

The ED problem assumes that the amount of power to be supplied by a given set of units is constants for a given interval of time and attempts to minimize cost of supplying this energy subject to constraints of the generating units. Therefore, it is concerned with the minimization of total cost incurred in the system and constraints over the entire dispatch period (Abido, 2001).

Therefore, the main aim in the economic load dispatch problem is to minimize the total cost of generating real power (production cost) at various stations while satisfying the loads and the losses in the transmission links.

3.3 Generator Operating Cost

The total cost of operation includes the fuel cost, cost of labour, supplies and maintenance. Generally, costs of labour, supplies and maintenance are fixed percentages of incoming fuel costs. The power output of fossil plants is increased sequentially by opening a set of valves to its steam turbine at the inlet. The throttling losses are large when a valve is just opened and small when it is fully opened. Figure 3.1 shows the simple model of a fossil plant dispatching purposes.

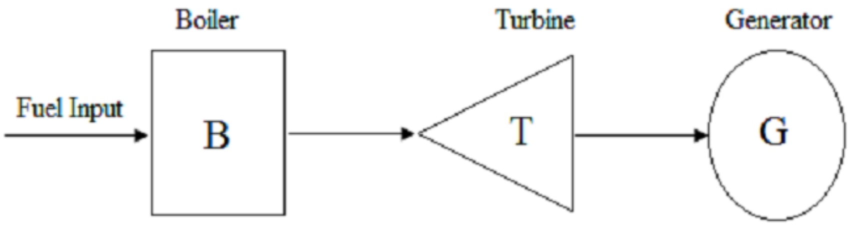

Figure 3.1: Simple Model of a Fossil Plants

Source: (Saadat, 2010)

The primary concern of ED problem is to minimize of its objective function. The objective function is formulated as below, where F is total fuel cost, N is number of generating unit and $F_i\,(P_{Gi})$ is operating fuel cost of generating unit i.

$$\min(F_T) = \min \sum_{i=1}^{N} F_i(P_{Gi}) \tag{3.1}$$

The generator cost curve is represented by quadratic functions and the total fuel cost $F_i\,(P_G)$ in (\$/h) can be expressed as below (Saadat, 2010):

$$F_i(P_{Gi}) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \tag{3.2}$$

Where N is the number of generators; a_i, b_i, c_i are the cost coefficients of the *i-th* generator and P_G is the vector of real power outputs of generators.

3.4 ED with Losses Consideration

When transmission distance is very small and load density is very high, transmission losses may be neglected and the optimal dispatch of generation is achieved with all plants operating at equal incremental production cost. However, in the large interconnected network where power is transmitted over a long distances with low density areas, transmission losses are major factor and affect the optimum dispatch of generation.

One common practice for including the effect of transmission losses is to express the total transmission loss as a quadratic function of the generator power outputs (Saadat, 2010). The simplest quadratic form is

$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00} \tag{3.3}$$

where,

N = number of generators
P_{Gj} = the output generation of unit j (MW).
B_{ij} = the ij^{th} element of the loss coefficient square matrix.
B_{i0} = the i^{th} element of the loss coefficient.
B_{00} = the loss coefficient constant.

3.5 Practical Operation Constraints of Generator

Practically, the actual economic dispatch problem is non-convex in nature due to valve point effect, ramp rate limit, prohibited operating zones, power generation limits, balance constraints and the transmission with losses consideration as previously explained. Therefore, the fuel cost curve is not monotonically increasing nature or of piecewise quadratic as previous assumptions. These simplifying assumptions result in an inaccurate dispatch. Hence for the accurate dispatch, all the constraints, non-convexity, and discontinuities stated as below must be taken into account to achieve true economic operation.

3.5.1 Ramp Rate Limit

Ramp Rate Limit (RRL) restricts the operating range of all the on line units for adjusting the generator operation between two operating periods. The generation can be changed according to the increasing and decreasing ramp rate limits only. The inequality constraints due to RRL for unit generation changes are given in equation (3.4). When the generator units are online, there exist three possible situations as shown in Figure 3.2.

- In the time interval *t-1* to *t*, the unit is operating in a steady state.
- The unit increases its power generation when the time interval is increased from *t-1* to *t*.
- When the time interval is increased from *t-1* to *t*, the unit decreases its power generation.

From the above situations, the inequality constraints due to ramp rate limits can be written as:

$$P_{Gi} - P_{Gi}^{0} \leq UR_i \qquad \text{if generation increases} \tag{3.4}$$

$$P_{Gi}^{o} - P_{Gi} \leq DR_i \qquad \text{if generation decreases} \tag{3.5}$$

The generator operation constraints with the ramp rate limit now expressed as:

$$\max(P_{Gi}^{\min}, P_{Gi}^{0} - DR_i) \leq P_{Gi} \leq \min(P_{Gi}^{\max}, P_{Gi}^{0} + UR_i) \tag{3.6}$$

Where P_{Gi} is the current output power and P_{Gi}^{0} is the previous output power. UR_i is the up ramp limit of the i^{th} generator (MW/time-period); and DR_i is the down ramp limit of the i^{th} generator (MW/time-period).

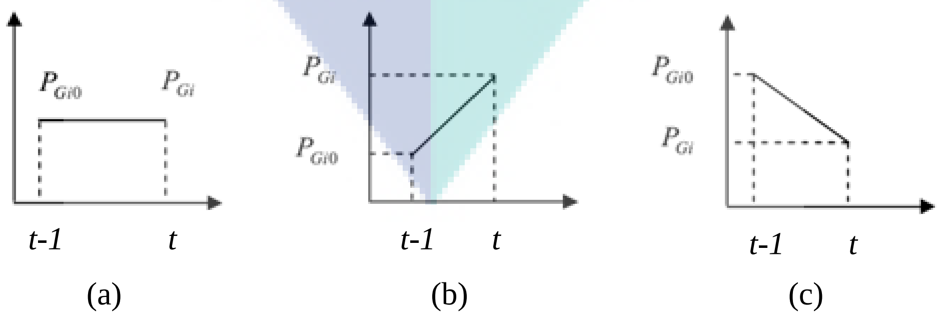

Figure 3.2: (a) Steady state operation, (b) Increasing the level of power generation and (c) Decreasing the level of power generation

Source: (Kothari and Dhillon, 2004)

3.5.2 Prohibited Operating Zones

A generation's unit may have Prohibited Operating Zone (POZ) due to the physical limitations of power plant components (e.g. steam valve operations or vibration in the shaft bearings.). The prohibited zones create a gap on the cost curves and cause discontinuity on the cost curve as in Figure 3.3. Usually, each prohibited region makes the decision space separate into disjoint subsets which then constitute a non-convex decision space. For a prohibited zone, the unit can only operate above or below the zone. Therefore, the corresponding economic dispatch problem becomes a non-convex optimization problem. The feasible operating zones of unit i can be described as follows:

$$\begin{aligned} &P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi,1}^{lower} \\ &P_{Gi,j-1}^{upper} \leq P_{Gi} \leq P_{Gi,j}^{lower},\ j = 2,3,..,PZ_i \\ &P_{Gi,PZ_i}^{upper} \leq P_{Gi} \leq P_{Gi}^{\max} \end{aligned} \tag{3.7}$$

where:

j	Number of prohibited zones of unit i
P_{Gi}	Output power of generator i
$P_{Gi}^{\min}$	Minimum power output limit of generator i
$P_{Gi}^{\max}$	Maximum power output limit of generator i
$P_{Gi,j}^{lower}$ & P_{Gi,PZ_i}^{upper}	Lower and upper boundaries of prohibited operation zone j

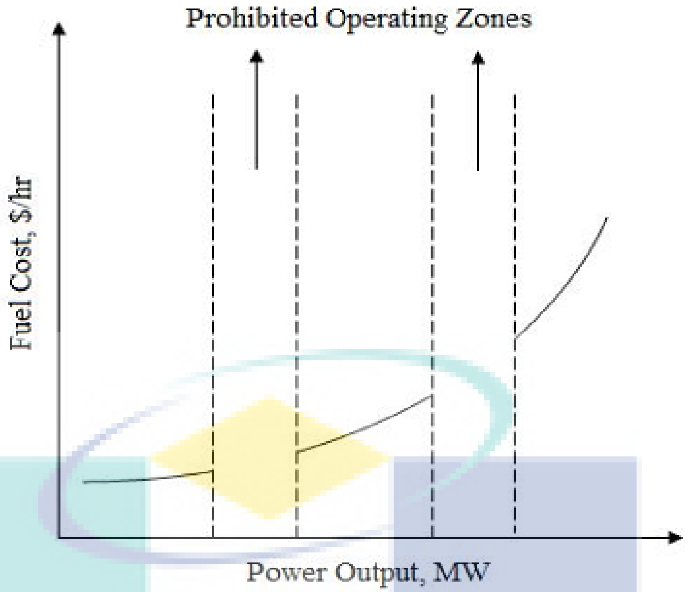

Figure 3.3: Fuel cost curve with prohibited zones

Source: (M. Vanitha, 2012)

3.5.3 Generation Limit Constraints

For stable operation, the real power output of each generator is restricted by lower and upper limits as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad i = 1,2,\ldots,N \tag{3.8}$$

Where:

$P_{Gi}^{\min}$	Minimum power output limit of generator i
P_{Gi}	Output power of generator i (MW)
$P_{Gi}^{\max}$	Maximum power output limit of generator i

3.5.4 Balance Constraints

The total output power generation is the sum of the total power demand, P_D and total power losses, P_{loss}. Hence, the total output power is shown in equation (3.9):

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_{loss} = 0 \tag{3.9}$$

3.5.5 Valve Point Loading Effects

To control every generators output power, the power plant employs several valves. The valve point loading effect occurs when each steam admission valve in a turbine starts to open, thus producing a rippling effect on the cost curve as depicted in the Figure 3.4. To account this effect in the economic load dispatch problem, a sinusoidal function is added to the quadratic cost function as follows:

$$F_T = \sum_{j=1}^{N} \alpha_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| e_i \times \sin\left(f_i \times \left(P_{Gi}^{\min} - P_{Gi} \right) \right) \right| \tag{3.10}$$

Where e_i and f_i are the coefficients of i^{th} generator with valve point loading.

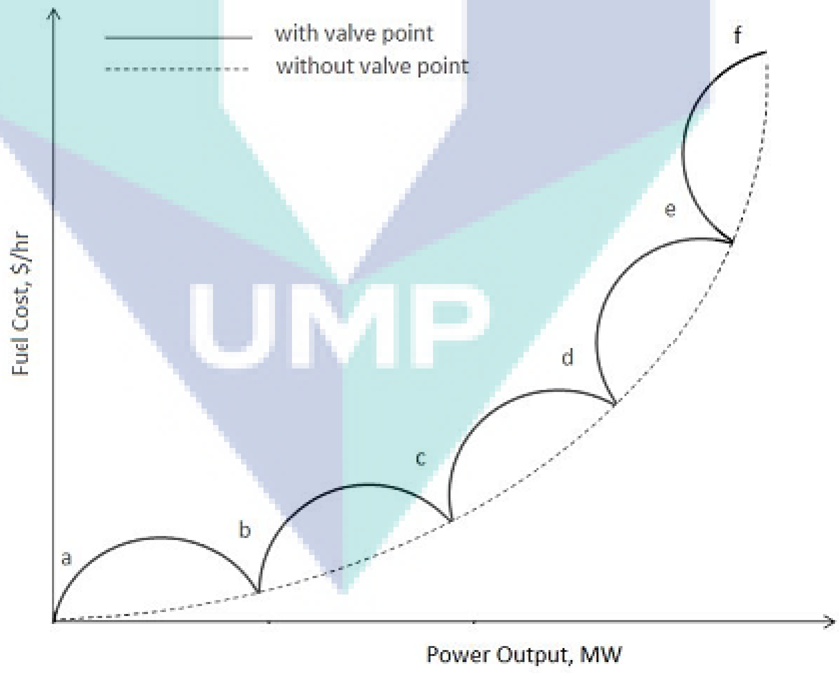

Figure 3.4: Fuel cost curve under valve point loading

Source: (M. Vanitha, 2012)

Where *a*, *b*, *c*, *d*, *e* and *f* are the opening of multiple valves in a steam turbine.

3.6 Mathematical Model of Grey Wolf Optimizer

The Grey Wollf Optimizer (GWO) algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented.In this section, the mathematical models of social hierarchy, tracking, encircling and attacking prey are provided.

3.6.1 Social Hierarchy

From the social hierarchy of grey wolf, the fittest solution is considered as the alpha, α. Consequently, the second and third best solutions are named beta, β and delta, δ respectively. The rest of the candidate solutions are assumed to be omega, ω. In the GWO algorithm the hunting (optimization) is guided by α, β, and δ. The ω wolves will follow these three wolves (Mirjalili and Lewis, 2014b).

3.6.2 Encircling Prey

When the wolves do hunting, they tend to encircle their prey. The following equations depicted the encircling behavior :

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \tag{3.11}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{3.12}$$

where $\vec{D}$ is position of each hunter from ω or any other hunters, t is the current iteration, $\vec{X}$ is the position vector of grey wolf, X_p is the position of the prey and $\vec{A}$ and $\vec{C}$ are coefficient vectors calculated as below:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{3.13}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{3.14}$$

Where r_1 and r_2 are random vectors [0, 1] and is linearly decreased from 2 to 0 over the course of iterations. The three best solutions (X_1, X_2, and X_3) are saved including the latest positions of omegas according to the current best position. X_1 is the best position of α, X_2 is the best position of β, and X_3 is the best position of δ. The final position $X(t+1)$, is defined by the positions of alpha, beta, and delta in the search space. These situations are expressed in the following expressions:

$$\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \\ \vec{D}_\beta &= \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \\ \vec{D}_\delta &= \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \end{aligned} \tag{3.15}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \left(\vec{X}_\alpha\right), \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \left(\vec{X}_\beta\right), \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \left(\vec{X}_\delta\right) \end{aligned} \tag{3.16}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{3.17}$$

To sum up, the optimization approach for GWO is starting with creating a random population of grey wolves which can be called as candidates of solution. During the simulation, alpha, beta and delta wolves estimate the possible position of the prey. Exploration and exploitation are guaranteed by the adaptive values of a and A. Candidate solutions are diverged from the prey if $\vec{A} > 1$ and converged towards the prey if $\vec{A} < 1$. Finally, GWO algorithm is terminated by the criterion that has been set initially.

3.7 Implementation of GWO in ED

The detailed algorithm for solving the economic load dispatch problem using GWO method is given as:

Step 1:

The individuals of the population are randomly initialized according to the limit of each unit ($P_{Gi}^{\min}$ and $P_{Gi}^{\max}$) including individual dimensions and number of populations, *N*. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2:

To each individual P_G of the population, employ the *B*-coefficient loss formula to calculate the transmission loss, P_{loss} as shown in equation (3.3).

Step 3:

Each set of solution in the space should satisfy the equality constraints. So equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation (3.9).

Step 4:

The evaluation function of each individual P_{Gi} , is calculated in the population using the equation (3.2).

while for equality constraint, when it is violated, the penalty factor, *PF* is implemented and embedded in the cost function, as follows:

$$F = (F) + PF \times abs\left[\left(\sum_{i=1}^{n} P_{Gi}\right) - P_D - P_{Loss}\right] \tag{3.18}$$

Step 5:

Compare each individual's evaluation value with its best solution. The three best solutions (X_1, X_2, and X_3) are saved, X_1 is the best position of α, X_2 is the best position of β, and X_3 is the best position of δ. The final position $X(t+1)$, which can be defined as $P_{Gi}(t+1)$ and expressed by the equation (3.17).

Step 6:

If the number of iterations reaches the maximum, then go to step 7. Otherwise, go to step 2.

Step 7:

The optimal generation power of each unit with the minimum total generation cost is generated.

The algorithm will continue until the maximum iteration is met and the optimum result is obtained. The flow chart of GWO is shown in Figure 3.5.

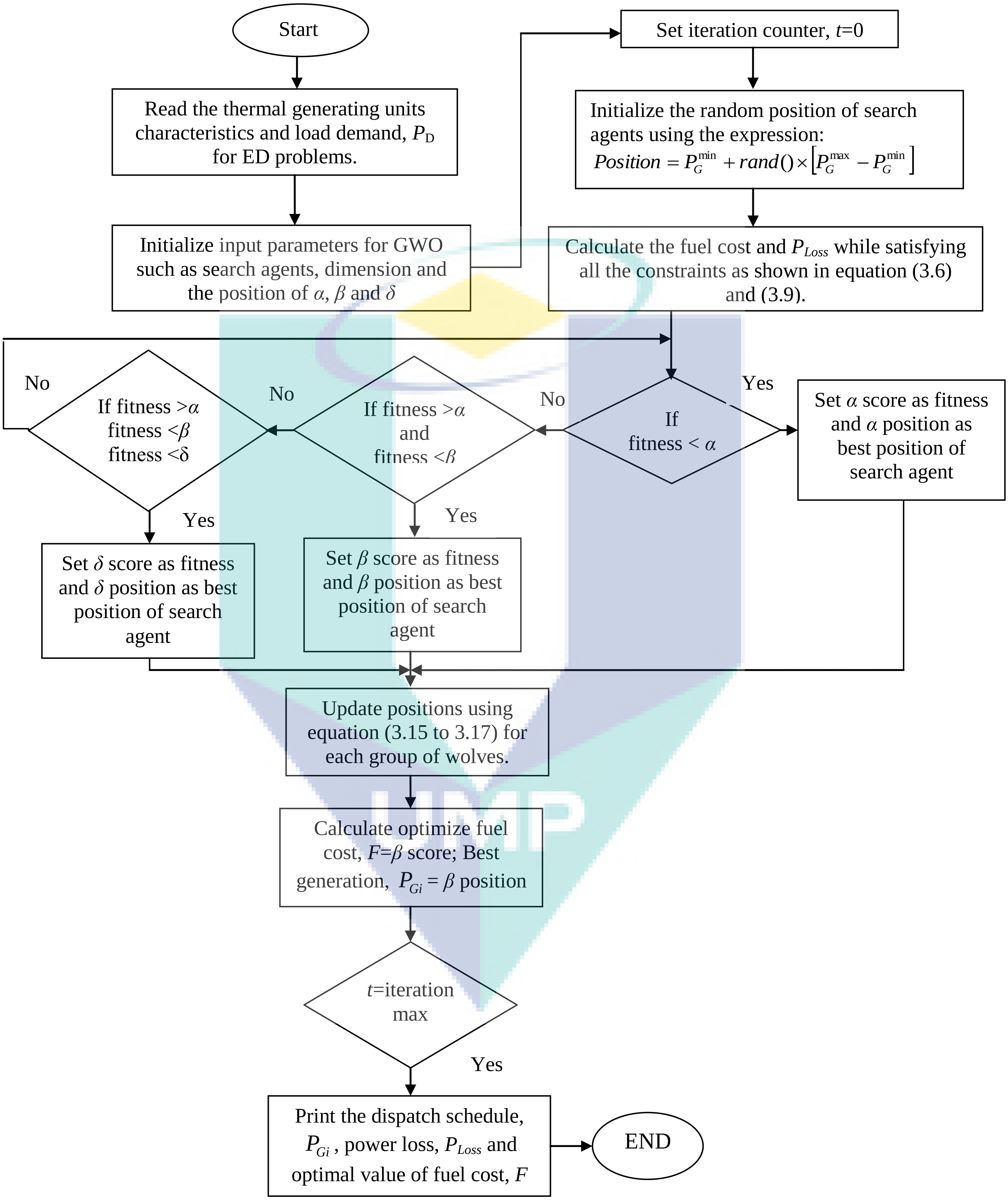

Figure 3.5: Flow Chart of GWO

3.8 Conclusion

In conclusion, based on the mathematical design of GWO, it shown that GWO is theoretically able to solve optimization problems, some points may be noted (Mirjalili and Lewis, 2014b):

- The proposed social hierarchy assists GWO to save the best solutions obtained so far over the course of iteration.
- The proposed encircling mechanism defines a circle-shaped neighborhood around the solutions which can be extended to higher dimensions as a hyper-sphere.
- The random parameters A and C assist candidate solutions to have hyper-spheres with different random radius.
- The proposed hunting method allows candidate solutions to locate the probable position of the prey.
- Exploration and exploitation are guaranteed by the adaptive values of a and A.
- The adaptive values of parameters a and A allow GWO to smoothly transition between exploration and exploitation.
- With decreasing A, half of the iterations are devoted to exploration ($|A|>1$) and the other half are dedicated to exploitation ($|A| < 1$).

CHAPTER 4

RESULT AND ANALYSIS

4.1 Introduction

In this chapter, in order to assess the efficiency of the proposed GWO method, seven cases are applied where the non-smooth objective functions are taken into account such as valve-point effects, prohibited zones and ramp rated limits. Implementation of GWO technique to solve ED problem in the power system are also discussed. In real life situations, ED will have non-smooth cost functions with equality and inequality constraints that make it a large-scale, highly constrained, non-linear and optimization problem. Thus, the proposed method opens up new approaches for solving ED problem.

4.2 Test Systems

In order to validate the proposed GWO, there are seven test cases been decided which are 3, 6, 13, 15, 20, 38 and 40-unit generating systems with a power demand of 850 MW, 1263 MW, 1800 MW, 2630 MW, 2500 MW, 6000 MW and 10500 MW respectively. The constraints of generation capacity, power balance with transmission loss, ramp rate limits and prohibited operating zones are considered for 6-unit and 15-unit system. 20-unit system is used with the generation capacity constraint and power balance constraint with transmission loss in contrast with 38-unit system which is without transmission loss. The valve point loading effects, generation capacity constraint and power balance constraints without transmission loss are considered for 3, 13 and 40-unit systems. In conclusion, GWO has been applied in all kind of economic dispatch problems and undoubtedly shown feasible results towards every test.

4.2.1 Case 1: 3-unit system

This test case study considered of three thermal units of generation with effects of valve-point as given Table 4.1 (Sinha, 2003). In this case, the load demand expected to be determined was P_D=850 MW. The results obtained for this case study are given Table 4.2, which shows that the GWO has approximately good solution for power demand of 850 MW. Besides, from the Table 4.2, it is clear that GA and PS approaches did not meet the load demand. Figure 4.1 shows the performance in the of fuel cost ($/h) vs. iteration for various numbers of agent of GWO. It is worth to highlight the robustness and efficiency of GWO because the best result is obtained by only applying 30 search agents and 30 iterations which is 8234.07 $/h. In order to test the stability of GWO, the system is tested using 30 search agents with 30 iterations and run for 30 times. Each reading per run is shown in Figure 4.2. The worst result obtained for 30 runs is 8241.6 $/h while the average is 8239.09 $/h and the best result is 8234.07 $/h. It shows that for each run the reading is drop in the range of 8234.07 $/h to 8241.6 $/h. Thus, it shows that GWO is quite stable in finding optimal solution for each run of simulation.

Table 4.1: Data for the three unit system (P_D=850 MW)

Unit	a_i	b_i	c_i	e_i	f_i	$P_{Gi}^{\min}$ (MW)	$P_{Gi}^{\max}$ (MW)
1	561	7.92	0.00156	300	0.0315	100	600
2	310	7.85	0.00194	200	0.042	100	400
3	78	7.97	0.00482	150	0.063	50	200

Table 4.2: Comparison among different methods for the 3-unit system

Method	Reference	P_1(MW)	P_2(MW)	P_3(MW)	P_D(MW)	Cost($/h)
GA	(Victoire & Jeyakumar, 2004)	398.7	50.1	399.6	848.4	8222.07
EP	(Victoire & Jeyakumar, 2004)	300.264	149.736	400	850	8234.07
EP-SQP	(Victoire & Jeyakumar, 2004)	300.267	149.733	400	850	8234.07
PSO	(Victoire & Jeyakumar, 2004)	300.268	149.732	400	850	8234.07
PSO-SQP	(Victoire & Jeyakumar, 2004)	300.267	149.733	400	850	8234.07
GAB	(Sinha, 2003)	-	-	-	-	8234.08
GAF	(Sinha, 2003)	-	-	-	-	8234.07
CEP	(Sinha, 2003)	-	-	-	-	8234.07
FEP	(Sinha, 2003)	-	-	-	-	8234.07
MFEP	(Sinha, 2003)	-	-	-	-	8234.08
IFEP	(Sinha, 2003)	-	-	-	-	8234.07
PS	(Mallikarjuna, Student, Reddy, & Hemakesavulu, 2013)	300.266	149.733	400	849.999	8234.05
GSA	(Duman, 2010)	300.21	149.795	399.996	850.001	8234.1
SA	(Vishwakarma & Dubey, 2013)	300.27	149.73	400	-	8234.07
Proposed GWO	(L. I. Wong, M. H. Sulaiman, M.R. Mohamed, 2015)	**300.267**	**149.733**	400	**850**	**8234.07**

Figure 4.1: Performance for various numbers of agents of GWO

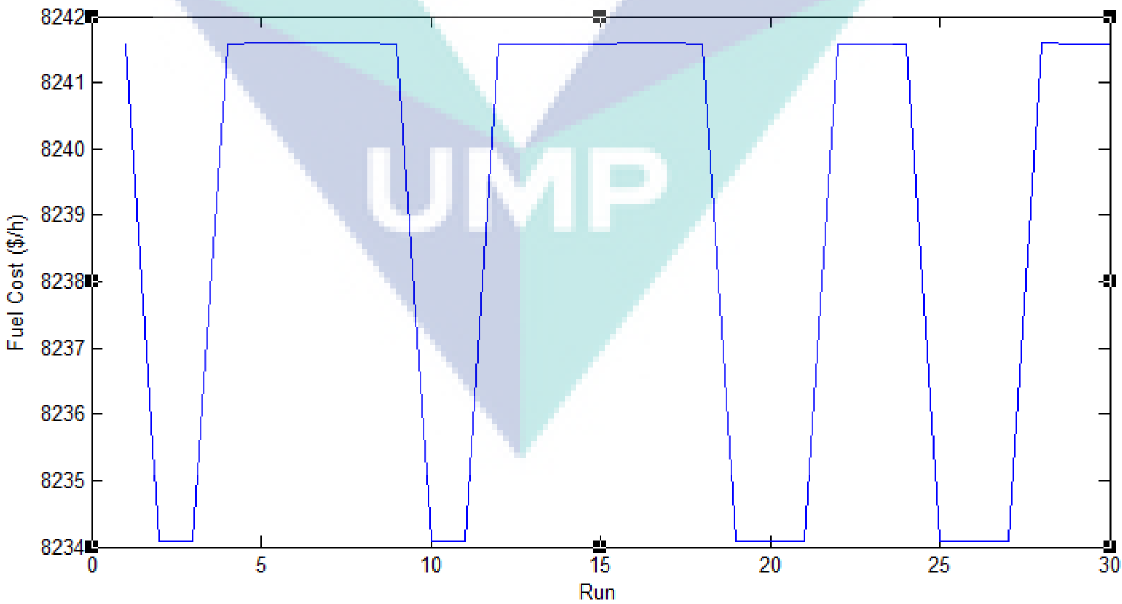

Figure 4.2: Performance of 30 Agents of GWO for 30 Free Running of Simulations

4.2.2 Case 2: 13-unit system

This test case consists of thirteen thermal units of generation with effects of valve-point as given Table 4.3 (Sinha, 2003). The increasing number of generating units makes the systems more complex and nonlinear compared to previous 3-unit system. The required load demands to be met by all the thirteen generating units is 1800 MW. Based on the convergence characteristic of GWO in Figure 4.3 and Figure 4.4, the performance of 40 search agents is better than other quantity of search agent because of its fast convergence. Thus, 40 search agents is fixed for every simulation. The results obtained for this case study are presented in Tables 4.4 and Table 4.5 respectively, which show that the simulation results obtained by GWO is slightly better compared among the reported methods in literature. Although the result is not the best, it still proves the feasibility of GWO in solving ED problem with valve point loading effects.

Table 4.3: Units Data for 13-unit System with Valve Point Loading

Unit	$P_{Gi}^{\min}$ **(MW)**	$P_{Gi}^{\max}$ **(MW)**	a_i	b_i	c_i	e_i	f_i
1	0	680	0.00028	8.1	550	300	0.035
2	0	360	0.00056	8.1	309	200	0.042
3	0	360	0.00056	8.1	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

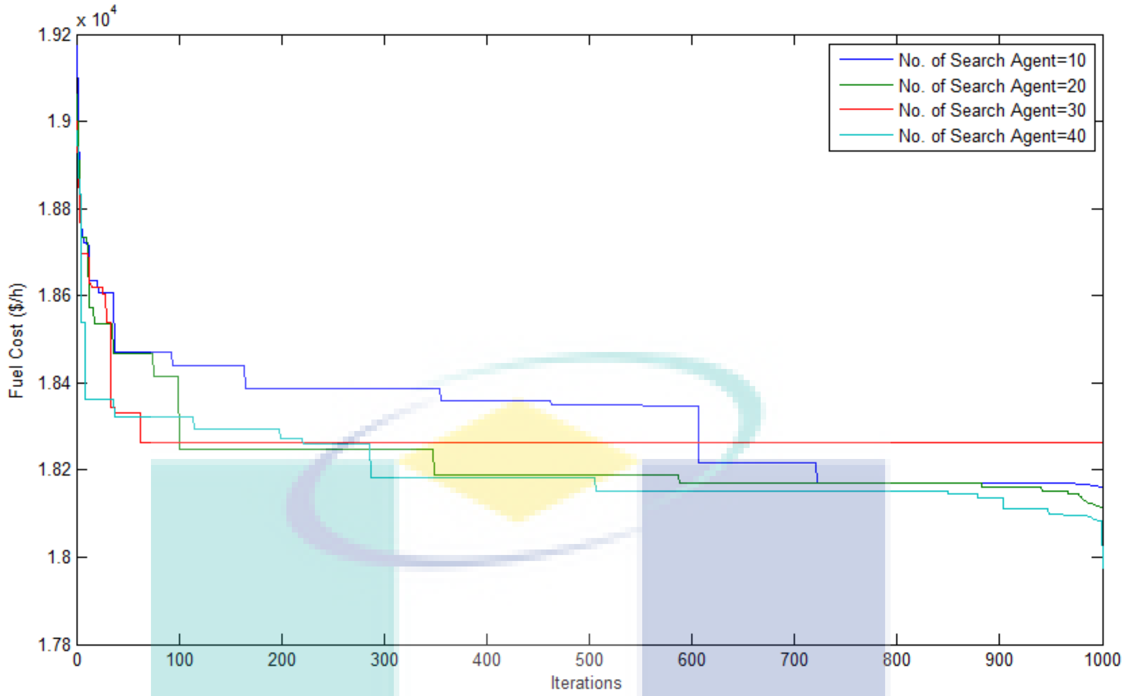

Figure 4.3: Convergence characteristic of proposed GWO with Various Numbers of Search Agent

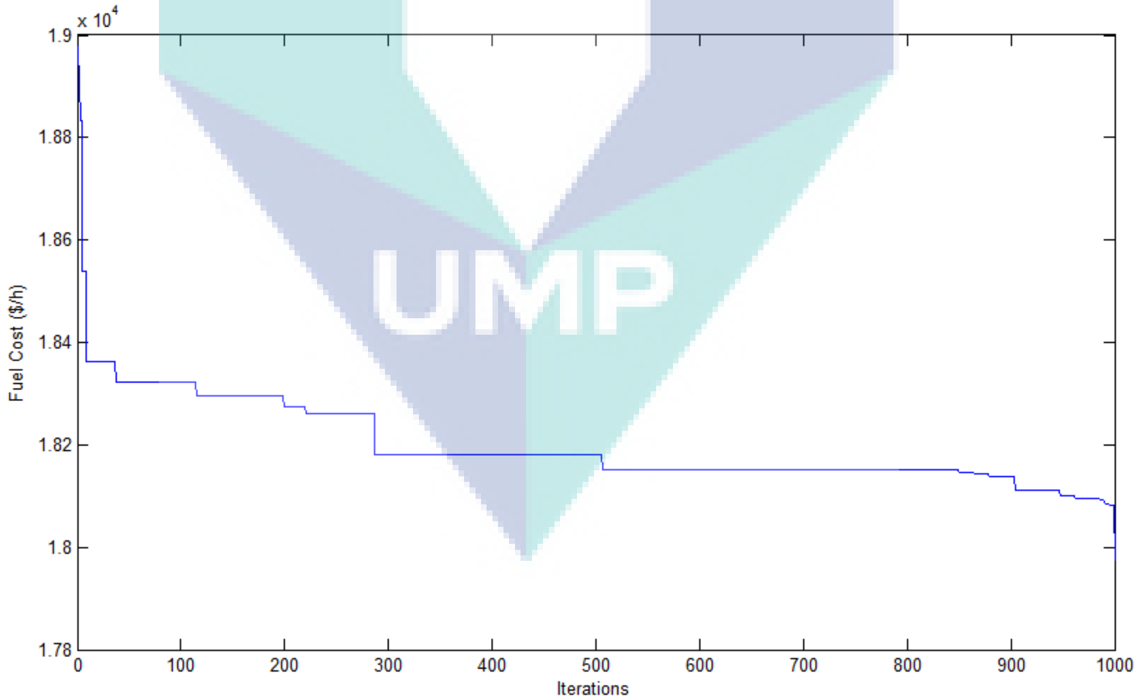

Figure 4.4: Convergence Characteristic of proposed GWO for Test Case 2 (1800 MW)

Table 4.4: Results Obtained by the Proposed Method for Test Case 2 (1800 MW)

Unit (MW)	**Proposed GWO**
P_1	628.32
P_2	223.11
P_3	298.86
P_4	60
P_5	60
P_6	109.86
P_7	60
P_8	60
P_9	109.86
P_{10}	40
P_{11}	40
P_{12}	55
P_{13}	55
Total Power Output(MW)	1800
Total Cost($/h)	**17972.94**

Table 4.5: Comparison of Proposed Method for Test Case 2 (1800 MW)

Method	Reference	Total Cost ($/h)
CEP	(Sinha, 2003)	18048.21
PSO	(Victoire & Jeyakumar, 2004)	18030.72
MFEP	(Sinha, 2003)	18028.09
FEP	(Sinha, 2003)	18018.00
IFEP	(Sinha, 2003)	17994.07
EP-SQP	(Victoire & Jeyakumar, 2004)	17991.03
HDE	(S. Wang et al., 2007)	17975.73
CGA-MU	(Chiang, 2005)	17975.34
GWO	(L. I. Wong, M. H. Sulaiman, M.R. Mohamed, 2015)	**17972.94**
PSO-SQP	(Gandomi, Yang, & Alavi, 2013)	17969.93
PS	(Mallikarjuna et al., 2013)	17969.17
UHGA	(Sinha, 2003)	17964.81
QPSO	(Zhisheng, 2010)	17964.00
IGA_MU	(Chiang, 2005)	17963.98
ST-HDE	(S. Wang et al., 2007)	17963.89
HGA	(He, Wang, & Mao, 2008)	17963.83
HQPSO(5)	(Coelho & Mariani, 2008)	17963.96
DE	(N Noman & Iba, 2008)	17963.83
GSA	(Duman, 2010)	17960.37

4.2.3 Case 3: 40-unit system

The 40-unit system consists of the fuel cost coefficient, minimum and maximum output of generator and power demand of 10500 MW. The objective function of total fuel cost and fuel cost curve of the units are both presented in quadratic cost functions. The input data for the 40-unit system are given in Table 4.6 (Sinha, 2003), where a_i, b_i and c_i are the cost coefficients. $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ are the minimum and maximum power generations respectively. Based on the analysis of the numbers of search agents towards the performance of GWO in Figure 4.5, eventually, 30 number of search agents is set in every simulation due to its better convergence. Figure 4.6 shows the performance of 30 search agents of GWO with 50000 iterations in 10 runs. The worst reading from the 10 runs of simulations is 121817.2 $/h and the best reading is 121488.4 $/h. It shows that

GWO is able to find the optimal solution in 10 runs. Therefore, the exploitation and exploration of GWO is quaranteed in searching for optimal solution.

The power output of the optimal fuel cost and demand are given in Table 4.7. It is also seen from the Table 4.8, that the best fuel cost for 40-unit system is achieved by FA (X. S. Yang, Hosseini, and Gandomi, 2012) method which is 121415.1 \$/hr. The proposed GWO which scored 121488.4 \$/hr is placed at 6th out of 32nd and improved by 2.65% in the comparison list. It shows that GWO is still available in solving large and complex valve point problem. Besides, Table 4.8 has shown the best, average and the worst total cost for each optimization techniques. GWO is quite stable to achieve the best performance in this test system.

Table 4.6: Data for Test Case 3

Generator	$P_{Gi}^{\min}$ (MW)	$P_{Gi}^{\max}$ (MW)	a_i	b_i	c_i	e_i	f_i
1	36	114	0.0069	6.73	94.705	100	0.084
2	36	114	0.0069	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.0114	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.6	455.76	200	0.042
10	130	300	0.00605	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.2	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.4	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.1	801.32	300	0.035
26	254	550	0.00277	7.1	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.0114	5.35	148.89	120	0.077
31	60	190	0.0016	6.43	222.92	150	0.063
32	60	190	0.0016	6.43	222.92	150	0.063
33	60	190	0.0016	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

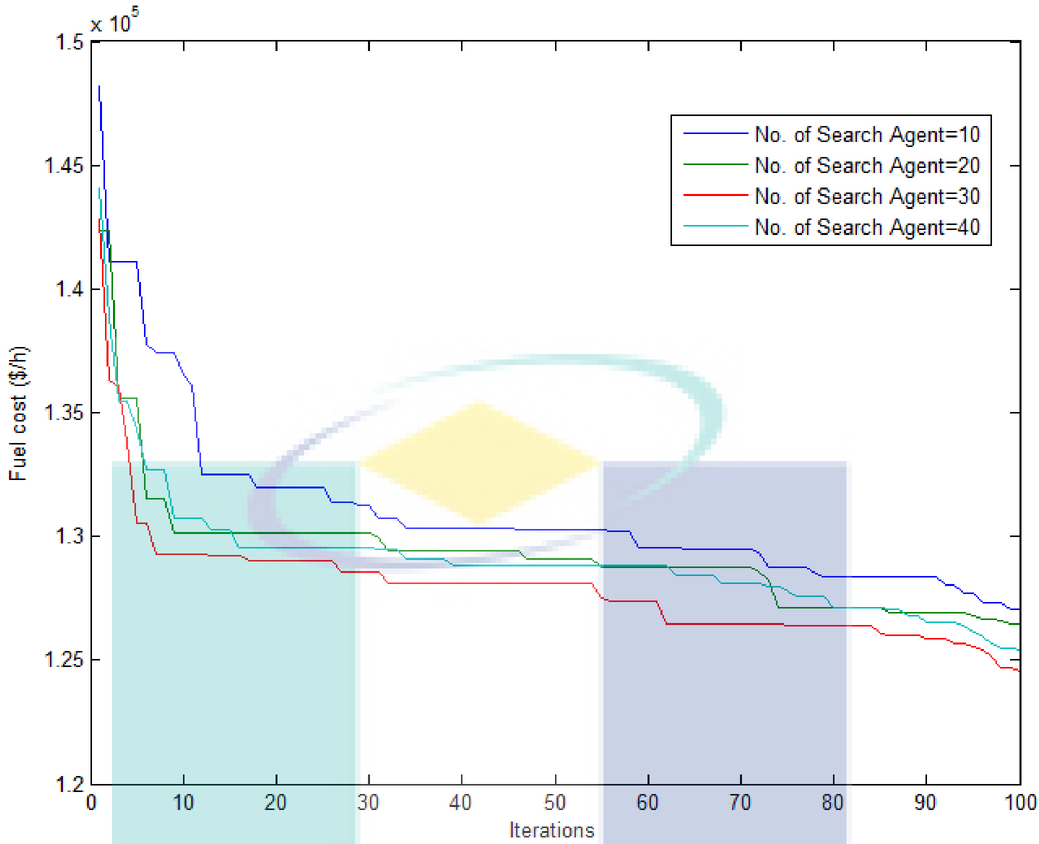

Figure 4.5: Convergence characteristic of proposed GWO with Various Numbers of Search Agent

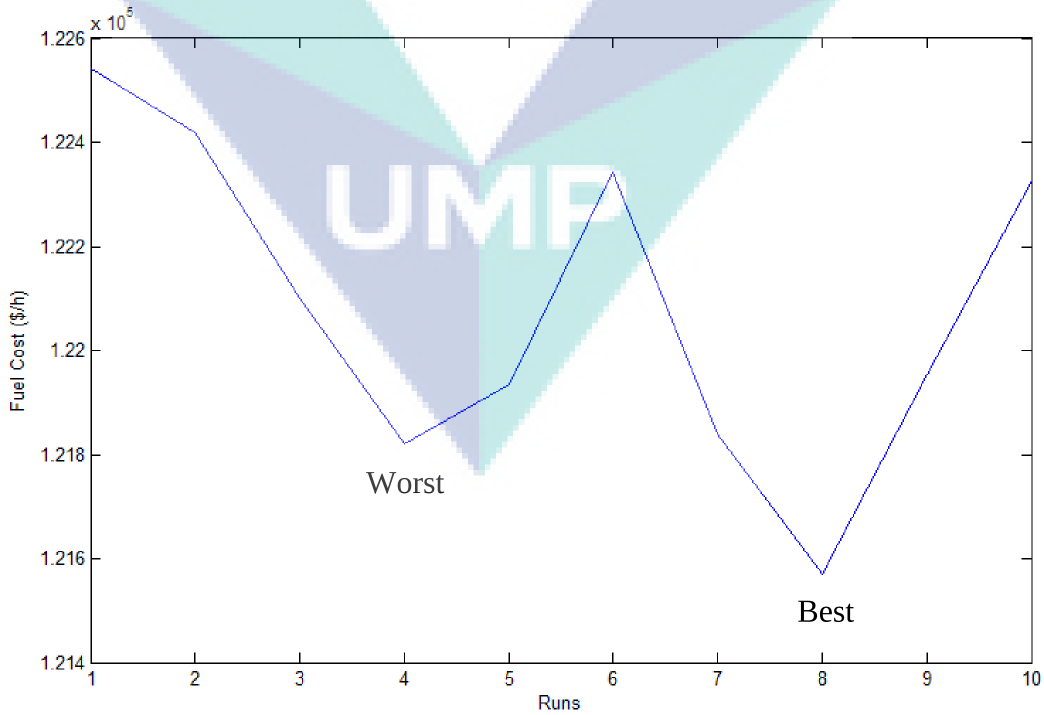

Figure 4.6: Performance of 30 Agents of GWO for 10 Free Running of Simulations

Table 4.7: Power Output of Generators of the Proposed GWO for the 40-unit Test System.

Unit	Power (MW)	Unit	Power (MW)
1	114	21	525.669066
2	113.2664051	22	527.011622
3	119.9971602	23	525.851589
4	180.3335967	24	526.128729
5	93.377924	25	523.409492
6	139.9997112	26	523.914352
7	300	27	11.2058529
8	299.9942709	28	10.1910836
9	299.9866398	29	10.7868009
10	130.1850191	30	88.3644704
11	94.05972815	31	189.996971
12	94.02519431	32	190
13	214.7628787	33	190
14	304.520957	34	199.995301
15	304.5204046	35	200
16	394.2859191	36	200
17	489.2957247	37	109.999705
18	489.6456483	38	109.996481
19	511.2929199	39	109.999302
20	511.5619014	40	511.317399
Total Generation (MW)		**10500**	
Total Generation cost ($/h)		**121488.4**	

Table 4.8: The Best, Average and Worst Results of Different ED Solution Methods for the 40-unit Test System.

Method	Reference	Generation cost ($/h)				
		Best	Average	Worst	Standard Deviation	No. of evaluation
HGPSO	(Ling, Iu, & Chan, 2008)	124797.1	126855.7	NA	1160.91	NA
SPSO	(Ling et al., 2008)	124350.4	126074.4	NA	1153.11	NA
PSO	(Victoire & Jeyakumar, 2004)	123930.5	124154.5	NA	NA	10,000
CEP	(Sinha, 2003)	123488.3	124793.5	126902.9	NA	NA
HGAPSO	(Ling et al., 2008)	122780	124575.7	NA	906.04	NA
FEP	(Sinha, 2003)	122679.7	124119.4	127245.6	NA	NA
MFEP	(Sinha, 2003)	122647.6	123489.7	124356.5	NA	NA
IFEP	(Sinha, 2003)	122624.4	123382	125740.6	NA	NA
TM	(Liu, Cai, & Member, 2006)	122477.8	123078.2	124693.8	NA	4050
EP–SQP	(Victoire & Jeyakumar, 2004)	122324	122379.6	NA	NA	10,000
MPSO	(Park & Lee, 2005)	122252.3	NA	NA	NA	NA
ESO	(Pereira-Neto et al., 2005)	122122.2	122558.5	123143.1	NA	75,000
HPSOM	(Ling et al., 2008)	122112.4	124350.9	NA	978.75	NA
PSO–SQP	(Victoire & Jeyakumar, 2004)	122094.7	122245.3	NA	NA	10,000
PSO-LRS	(A. I. Selvakumar & Thanushkodi, 2007)	122035.8	122558.5	123461.7	NA	20,000
Improved GA	(Ling & Leung, 2007)	121915.9	122811.4	123334	NA	100,000
HPSOWM	(Ling et al., 2008)	121915.3	122844.4	NA	497.44	NA
IGAMU	(Chiang, 2007)	121819.3	NA	NA	NA	NA
HDE	(S. Wang et al., 2007)	121813.3	122705.7	NA	NA	100
DEC(2)-SQP(1)	(dos Santos Coelho & Mariani, 2006)	121742	122295.1	122839.3	386.181	18,000
PSO	(A. Selvakumar & Thanushkodi, 2008)	121735.5	122513.9	123467.4	NA	20,000
APSO(1)	A. Selvakumar & Thanushkodi, 2008)	121704.7	122221.4	122995.1	NA	20,000
ST-HDE	(S. Wang et al., 2007)	121698.5	122304.3	NA	NA	100
NPSO-LRS	(A. I. Selvakumar & Thanushkodi, 2007)	121664.4	122209.3	122981.6	NA	20,000
APSO(2)	A. Selvakumar & Thanushkodi, 2008)	121663.5	122153.7	122912.4	NA	20,000
SOHPSO	(K. Chaturvedi, 2008)	121501.1	121853.6	122446.3	NA	62,500
GWO	(L. I. Wong, M. H. Sulaiman, M.R. Mohamed, 2015)	**121488.4**	**121639.6**	**121817.2**	**NA**	**50,000**
BBO	(Bhattacharya & Chattopadhyay, 2010a)	121479.5	121512.1	121688.7	NA	50,000
BF	(B. Panigrahi & Pandi, 2008)	121423.6	121814.9	124876	NA	10,000
GA–PS–SQP	(Alsumait, Sykulski, & Al-Othman, 2010)	121458	122039	NA	NA	1000
PS	(Al-Sumait, Al-Othman, & Sykulski, 2007)	121415.1	122332.7	125486.3	NA	1000
FA	(X. S. Yang et al., 2012)	121415.1	121416.6	121424.6	1.784	25,000

*NA: Not Available

4.2.4 Case 4: 6-unit system

The proposed GWO algorithm also has been tested on two test systems: 6 units and 15 units systems which both of them contain prohibited zones, ramp rate limits and transmission loss. The 6-unit system comprises 26 buses including 6 thermal units and 46 transmission lines. For this study, the load demand is 1263 MW. The characteristics of the six thermal units are given in (Z. Gaing, 2003) as shown in Table 4.9, Table 4.10 and *B* coefficients is shown in equation (4.1), (4.2) and (4.3). Based on the analysis of the numbers of search agents towards the performance of GWO in Figure 4.7, 30 number of search agents is sufficient in achieving better convergence. Figure 4.8 shows the performance of GWO for 20 runs of simulation. The result obtained for each run is really stable and drop in the range between 15442.3 $/h and 15442.7 $/h.

The best result of GWO compared with other recently published methods is shown in Table 4.12 respectively. The result obtained satisfying the system constraints, such as ramp rate limits and prohibited operating zones of units. Besides, the result is the best compared to others optimization techniques. The robustness of GWO deals with ramp rate limit, prohibited zone and transmission loss system is worth to emphasize here because the mentioned result is obtained by only 100 iterations with 30 populations. This indicated that GWO optimization has better convergence rate and obviously superior in economic dispatch with practical constraints.

Table 4.9: Generating Unit Capacity and Coefficients

Unit	$P_{Gi}^{\min}$ (MW)	$P_{Gi}^{\max}$ (MW)	a_i	b_i	c_i
1	100	500	240	7	0.007
2	50	200	200	10	0.0095
3	80	300	220	8.5	0.009
4	50	150	200	11	0.009
5	50	200	220	10.5	0.008
6	50	120	190	12	0.0075

Table 4.10: Ramp Rate Limits and Prohibited Zones of Six Generating Units

Unit	$P_i^0(MW)$	$URi(MW/h)$	$DRi(MW/h)$	Prohibited Zones(MW)
1	440	80	120	[210 240] [350 380]
2	170	50	90	[90 110] [40 160]
3	200	65	100	[150 170] [210 240]
4	150	50	90	[80 90] [110 120]
5	190	50	90	[90 110] [140 150]
6	110	50	90	[75 85] [100 105]

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix} \tag{4.1}$$

$$B_{oi} = 1.0e^{-03} * \begin{bmatrix} -0.3908 & -0.1297 & 0.7047 & 0.0591 & 0.2161 & -0.6635 \end{bmatrix} \tag{4.2}$$

$$B_{oo} = 0.0056 \tag{4.3}$$

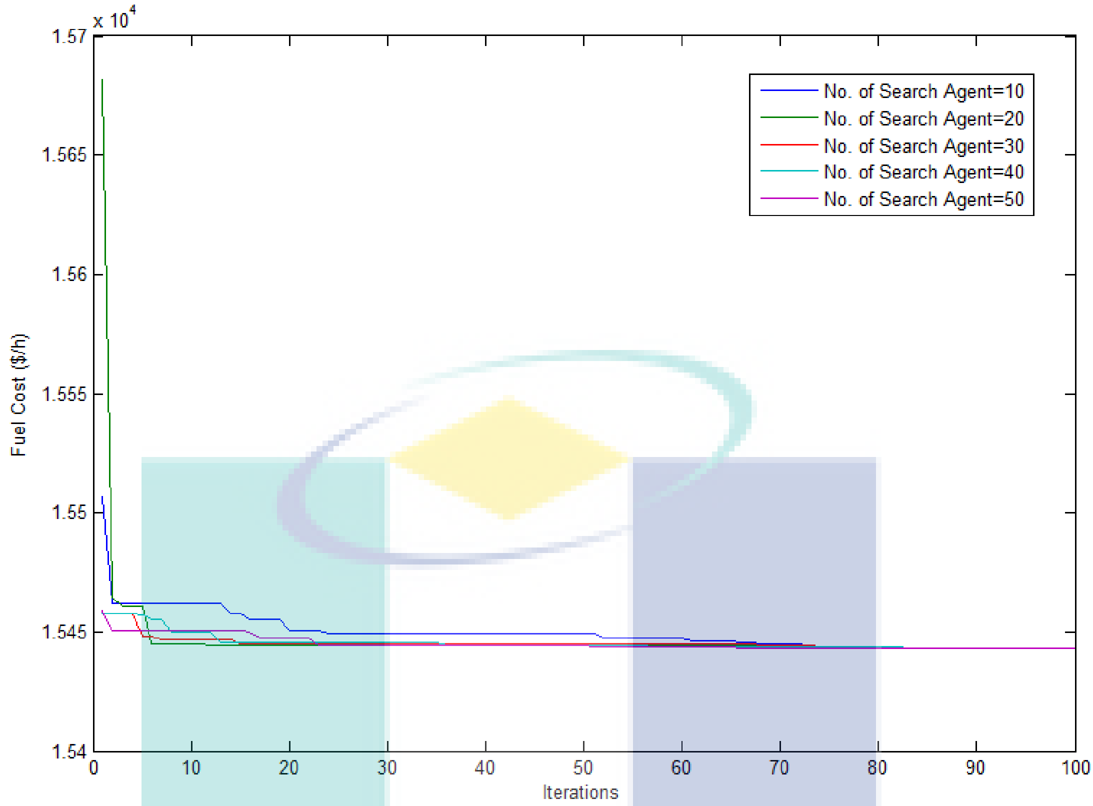

Figure 4.7: Convergence Curve of Various Numbers of Search Agent in 100 Iterations

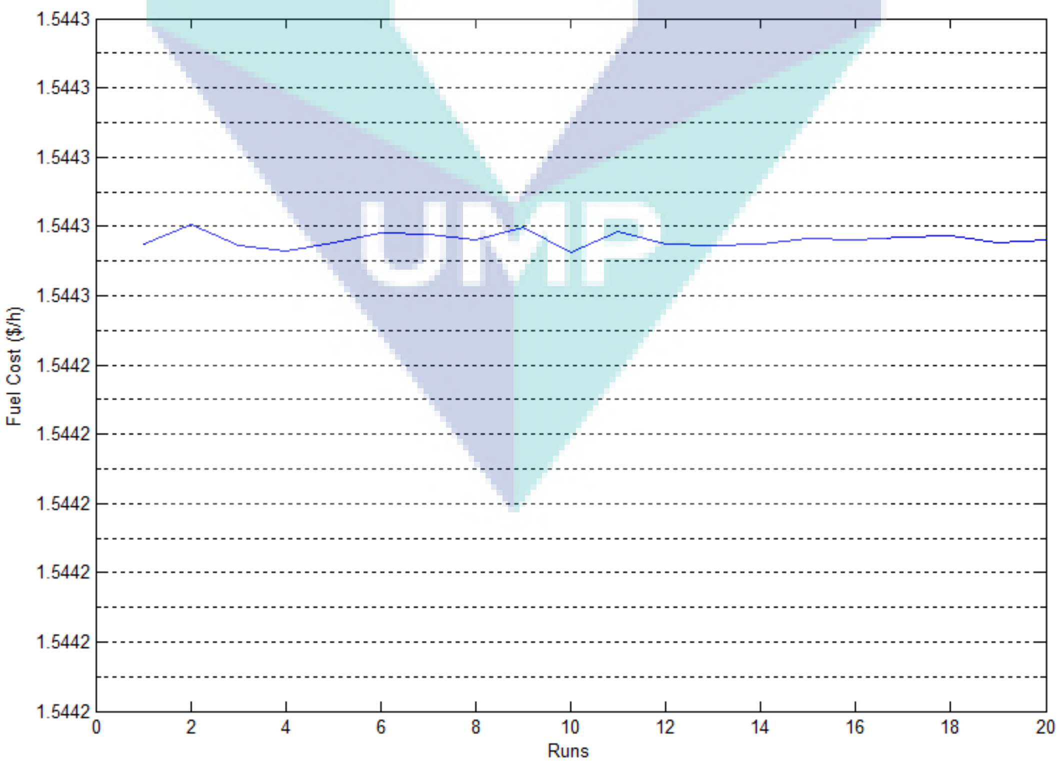

Figure 4.8: Performance of 30 Agents of GWO for 20 Free Running of Simulations

Table 4.11: Output Power of Generators for 6-unit System

Unit (MW)	GWO
P_1	447.1378
P_2	173.2883
P_3	264.2843
P_4	139.3006
P_5	165.2743
P_6	86.1249
Line Loss (MW)	12.4101
Total Output (MW)	1275.4
Cost ($/h)	15442.6618

Table 4.12: Comparison Methods for 6-unit System Result

Methods	Reference	Cost ($/h)
GWO	(L. I. Wong, M. H. Sulaiman, M.R. Mohamed, 2015)	15442.66
BBO	(Nazari & Hadidi, 2012)	15442.68
DS	(Herwan, 2013)	15443
MFA	(Sulaiman, Daniyal, & Mustafa, 2012)	15443
SOHPSO	(K. T. Chaturvedi, Pandit, & Srivastava, 2008)	15446.02
PSO	(Pereira-Neto et al., 2005)	15450
PSO-LRS	(A. I. Selvakumar & Thanushkodi, 2007)	15450
NPSO	(A. I. Selvakumar & Thanushkodi, 2007)	15450
NPSOLRS	(A. I. Selvakumar & Thanushkodi, 2007)	15450
GA	(Pereira-Neto et al., 2005)	15459

4.2.5 Case 5: 15-unit system

In this test system, all the mentioned practical constraints and nonlinear characteristics of the ED problem are included. The load demand is set to 2630 MW. The characteristic of this system can be obtained in (Z. Gaing, 2003) which ramp rate limits and prohibited operating zones shown in Table 4.13 and *B* loss coefficients are shown in equation (4.4) to (4.6). It can be seen that the prohibited operating zones embedded in the 4 units. They are unit 2, 5, 6 and 12. Table 4.14 and Table 4.15 show the output power of generators for 15-unit system and the comparison of various methods for 15-unit system. Figure 4.9 depicted the convergence of GWO with different quantity of search agent. Based on the observation from Figure 4.9, it verdicts that the number of search agent adequate for this test system is from 30 to 50. Definitely, faster convergence needs the more quantity of search agents. Figure 4.10 shows the performance of GWO for 15 runs. Figure 4.10 shown the results for each run of simulation drop in the range of 32687.57 to 32691.33 $/h. It shows the stability of GWO by getting the result for each run without tremendous difference. Based on 6-unit and 15-unit system results, noticed that GWO present obviously outstanding in ED problem which bear with ramp rate limit and prohibited zones.

Table 4.13: Ramp Rate Limits and Prohibited Zones of Fifteen Generating Units

Unit	$P_i^0(MW)$	$URi(MW/h)$	$DRi(MW/h)$	Prohibited Zones(MW)
1	400	80	120	–
2	300	80	120	[185 225][305 335][420 450]
3	105	130	130	–
4	100	130	130	–
5	90	80	120	[180 200][305 335][390 420]
6	400	80	120	[230 255][365 395][430 455]
7	350	80	120	–
8	95	65	100	–
9	105	60	100	–
10	110	60	100	–
11	60	80	80	–
12	40	80	80	[30 40][55 65]
13	30	80	80	–
14	20	55	55	–
15	20	55	55	-

$$B_{ij} = 10^{-3} * \begin{bmatrix} 1.4 & 1.2 & 0.7 & -0.1 & -0.3 & -0.1 & -0.1 & -0.1 & -0.3 & -0.5 & -0.3 & -0.2 & 0.4 & 0.3 & -0.1 \\ 1.2 & 1.5 & 1.3 & 0.0 & -0.5 & -0.2 & 0.0 & 0.1 & -0.2 & -0.4 & -0.4 & -0.0 & -0.4 & 1.0 & -0.2 \\ 0.7 & 1.3 & 7.6 & -0.1 & -1.3 & -0.9 & -0.1 & 0.0 & -0.8 & -1.2 & -1.7 & -0.0 & -2.6 & 11.1 & -2.8 \\ -0.1 & 0.0 & -0.1 & 3.4 & -0.7 & -0.4 & 1.1 & 5.0 & 2.9 & 3.2 & -1.1 & -0.0 & 0.1 & 0.1 & -2.6 \\ -0.3 & -0.5 & -1.3 & -0.7 & 9.0 & 1.4 & -0.3 & -1.2 & -1.0 & -1.3 & 0.7 & -0.2 & -0.2 & -2.4 & -0.3 \\ -0.1 & -0.2 & -0.9 & -0.4 & 1.4 & 1.6 & -0.0 & -0.6 & -0.5 & -0.8 & 1.1 & -0.1 & -0.2 & -1.7 & 0.3 \\ -0.1 & 0.0 & -0.1 & 1.1 & -0.3 & -0.0 & 1.5 & 1.7 & 1.5 & 0.9 & -0.5 & 0.7 & -0.0 & -0.2 & -0.8 \\ -0.1 & 0.1 & 0.0 & 5.0 & -1.2 & -0.6 & 1.7 & 16.8 & 8.2 & 7.9 & -2.3 & -3.6 & 0.1 & 0.5 & -7.8 \\ -0.3 & -0.2 & -0.8 & 2.9 & -1.0 & -0.5 & 1.5 & 8.2 & 12.9 & 11.6 & -2.1 & -2.5 & 0.7 & -1.2 & -7.2 \\ -0.5 & -0.4 & -1.2 & 3.2 & -1.3 & -0.8 & 0.9 & 7.9 & 11.6 & 20.0 & -2.7 & -3.4 & 0.9 & -1.1 & -8.8 \\ -0.3 & -0.4 & -1.7 & -1.1 & 0.7 & 1.1 & -0.5 & -2.3 & -2.1 & -2.7 & 14.0 & 0.1 & 0.4 & -3.8 & 16.8 \\ -0.2 & -0.0 & -0.0 & -0.0 & -0.2 & -0.1 & 0.7 & -3.6 & -2.5 & -3.4 & 0.1 & 5.4 & -0.1 & -0.4 & 2.8 \\ 0.4 & 0.4 & -2.6 & 0.1 & -0.2 & -0.2 & -0.0 & 0.1 & 0.7 & 0.9 & 0.4 & -0.1 & 10.3 & -10.1 & 2.8 \\ 0.3 & 1.0 & 11.1 & 0.1 & -2.4 & -1.7 & -0.2 & 0.5 & -1.2 & -1.1 & -3.8 & -0.4 & -10.1 & 57.8 & -9.4 \\ -0.1 & -0.2 & -2.8 & -2.6 & -0.3 & 0.3 & -0.8 & -7.8 & -7.2 & -8.8 & 16.8 & 2.8 & 2.8 & -9.4 & 128.3 \end{bmatrix} \quad (4.4)$$

$$Boi = 10^{-3} * \begin{bmatrix} -0.1 & -0.2 & 2.8 & -0.1 & 0.1 & -0.3 & -0.2 & -0.2 & 0.6 & 3.9 & -1.7 & 0.0 & -3.2 & 6.7 & -6.4 \end{bmatrix} \quad (4.5)$$

$$B_{oo} = 0.0055 \quad (4.6)$$

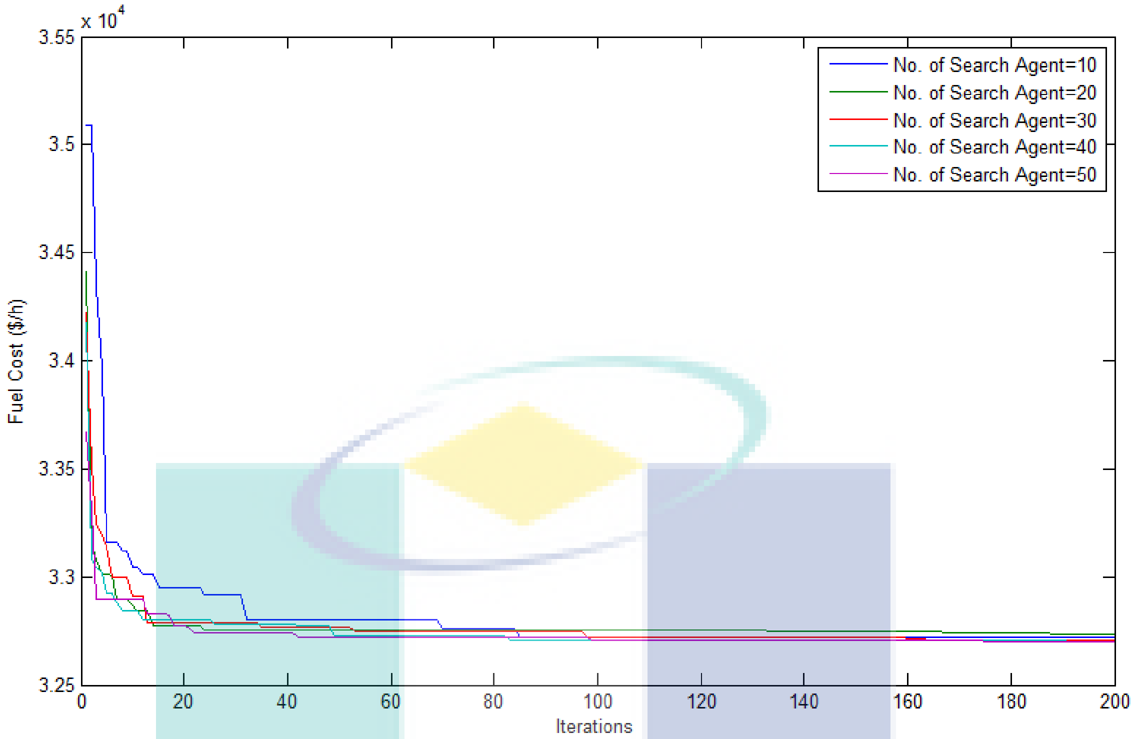

Figure 4.9: Convergence Curve of Various Numbers of Search Agent in 100 Iterations

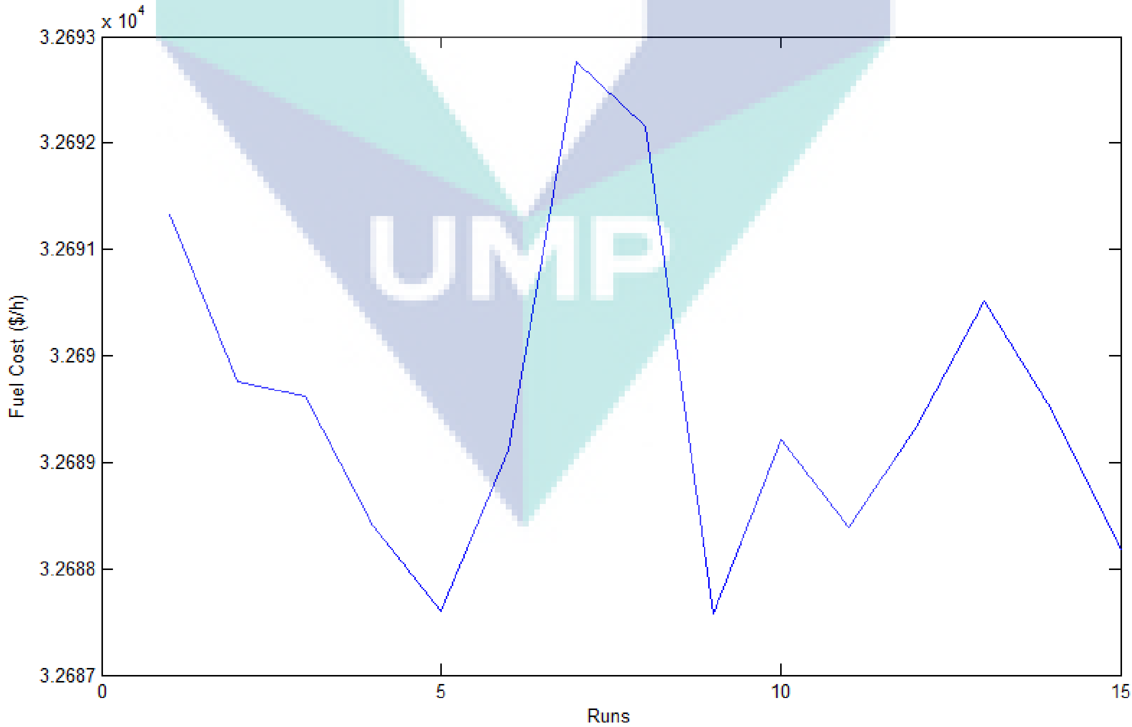

Figure 4.10: Performance of 50 Agents of GWO for 15 Free Running of Simulations

Table 4.14: Best Power Dispatch Obtained by Proposed GWO for 15-unit System

Units	**GWO**
P_1	455
P_2	380
P_3	130
P_4	130
P_5	170
P_6	460
P_7	430
P_8	90.3011
P_9	38.8784
P_{10}	159.9891
P_{11}	79.9993
P_{12}	79.9979
P_{13}	25.0016
P_{14}	15.0015
P_{15}	15.0029
Total output (MW)	2659.2
Loss (MW)	30.0634
Cost ($/h)	32687

Table 4.15: Comparison of Different Methods' Solution for 15-unit System

Methods	**Reference**	**Cost ($/h)**
GWO	(L. I. Wong, M. H. Sulaiman, M.R. Mohamed, 2015)	32687
DS	(Herwan, 2013)	32688
BBO	(Nazari & Hadidi, 2012)	32558.7
GA	(Z. L. Gaing, 2003)	33113
PSO	(Z. L. Gaing, 2003)	32858
ESO	(Pereira-Neto et al., 2005)	32568.5
SPSO	(K. T. Chaturvedi et al., 2008)	32798.7
PC_PSO	(K. T. Chaturvedi et al., 2008)	32775.4
SOH_PSO	(K. T. Chaturvedi et al., 2008)	32751.4

4.2.6 Case 6: 20-unit system

20-unit system with transmission loss is implemented to show the comprehensiveness of GWO. The input data is taken from Ching-Tzong and Chien Tung in 2000 (Amjady & Nasiri-Rad, 2009). The system data are tabulated in Appendix A and Table 4.16 (Amjady & Nasiri-Rad, 2009). The valve point loading effect is not considered for this system but transmission loss is considered. For this test system load demand is 2500 MW. The results reported in the literature reviews. BBO, LI, HM, QP and GAMS, ABCNN, ABC, CS and Firefly are compared with the GWO-based results and the potential benefit of the GWO as an optimizing algorithm for this specific application is established.

Table 4.17 shown the performance of GWO with various numbers of search agent and it depicted that 20 numbers of search agents achieved better convergence. Figure 4.11 is the convergence curve of 20 units of search agents and 300 iterations. It shown 20 units of search agents is enough for this system and it converged to optimal solution at last. Therefore, based on the analysis from Table 4.17 and Figure 4.11, 20 numbers of search agents is chosen for this test system. In order to test the stability of GWO, the system is tested using 20 search agents with 1000 iterations and run for 10 times of simulations. Each reading per run is recorded in Table 4.18. Figure 4.12 is generated from the reading in Table 4.18. The worst result obtained for 10 runs is 60415.09449 $/h while the best solution is 60413.84779 $/h. The difference between the best solution and the worst solution is 1.2467 $/h. Thus, from Table 4.18 and Figure 4.12, it shows that GWO is stable for each time of simulation and is able to provide each solution approximately near to optimal solution per run.

Total power generation of each unit and total transmission loss are shown in Table 4.19. Besides, the total cost for all mentioned techniques are tabulated in the Table 4.20. It can be observed that the minimum costs achieved by the GWO based method for test system is 60413.0014 $/h. It can be noted that the power generated by GWO are within the range of the minimum and maximum bounds at each generator. Hence, it can be concluded that for all the mentioned test system the performance of the GWO is found to be the best one.

Table 4.16: System Data for 20 Generators System

Unit	P_{Gi}^{min}(MW)	P_{Gi}^{max}(MW)	*ai*	b_i	c_i
1	150	600	0.00068	18.19	1000
2	50	200	0.00071	19.26	970
3	50	200	0.0065	19.8	600
4	50	200	0.005	19.1	700
5	50	160	0.00738	18.1	420
6	20	100	0.00612	19.26	360
7	25	125	0.0079	17.14	490
8	50	150	0.00813	18.92	660
9	50	200	0.00522	18.27	765
10	30	150	0.00573	18.92	770
11	100	300	0.0048	16.69	800
12	150	500	0.0031	16.76	970
13	40	160	0.0085	17.36	900
14	20	130	0.00511	18.7	700
15	25	185	0.00398	18.7	450
16	20	80	0.0712	14.26	370
17	30	85	0.0089	19.14	480
18	30	120	0.00713	18.92	680
19	40	120	0.00622	18.47	700
20	30	100	0.00773	19.79	850

Table 4.17: Performance of GWO with Various Numbers of Search Agent

No. of Search Agent	Total Cost($/h)
10	60417.19329
20	60414.60333
30	60415.59017
40	60415.13516
50	60414.6572

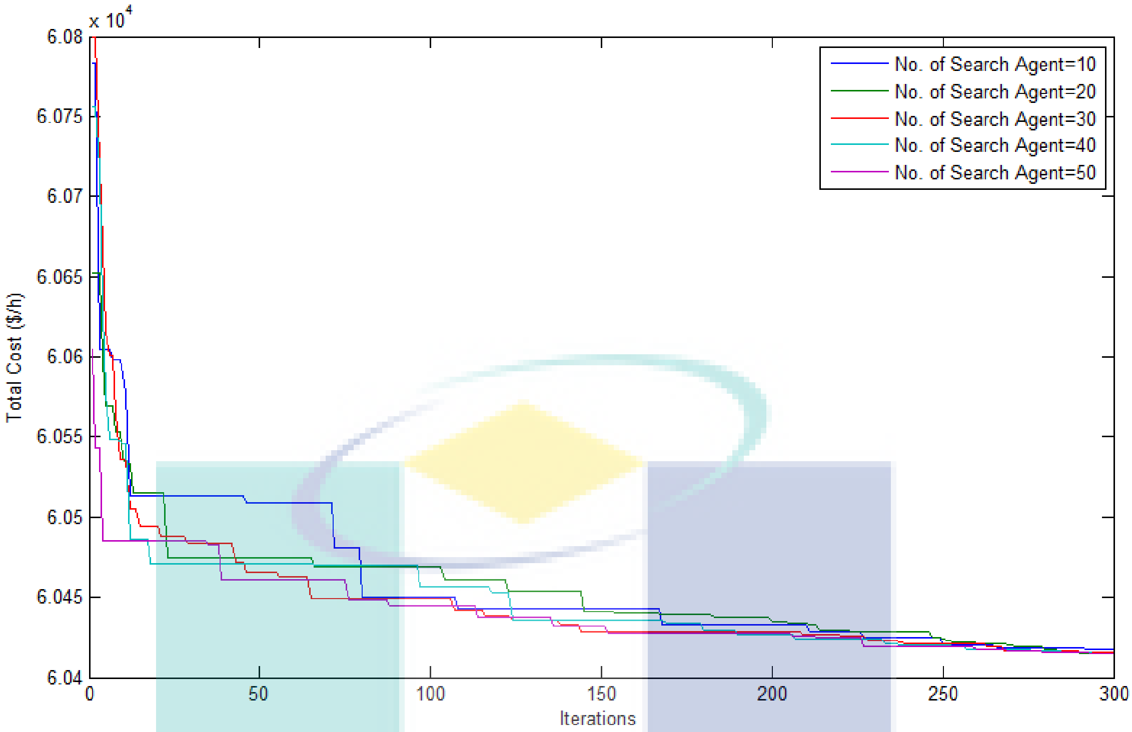

Figure 4.11: Convergence Curve of Various Numbers of Search Agent in 300 Iterations

Table 4.18: Performance of GWO for Each Run by Implementing 20 Search Agents with 1000 Iterations

Runs	Total Cost ($/h)
1	60414.06704
2	60415.09449
3	60414.08821
4	60413.94304
5	60414.31857
6	60414.22572
7	60414.01336
8	60414.07407
9	60415.45846
10	60413.84779

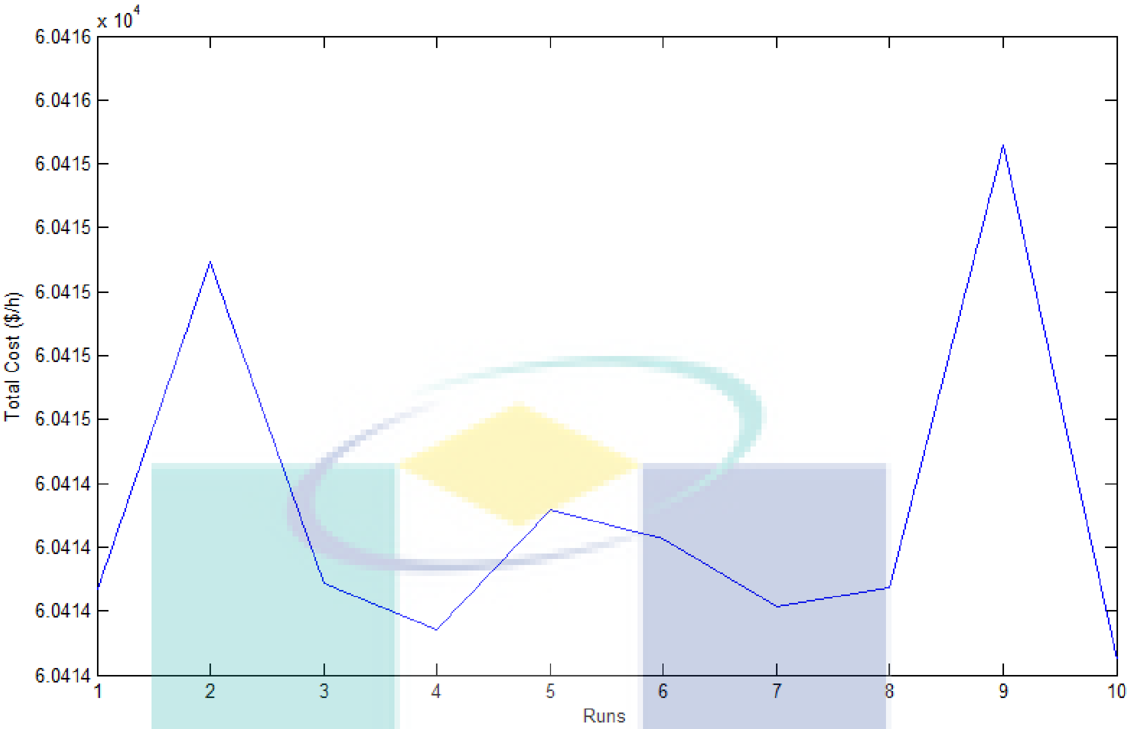

Figure 4.12: Performance of GWO for Each Run by Implementing 20 Search Agents with 10 runs

Table 4.19: Total Power Generation of Each Unit by Proposed GWO

Unit	GWO
P_1	599.999
P_2	160.161
P_3	50
P_4	50.0197
P_5	93.2573
P_6	26.7292
P_7	125
P_8	50.0177
P_9	108.672
P_{10}	54.5728
P_{11}	266.125
P_{12}	414.621
P_{13}	124.306
P_{14}	70.6027
P_{15}	98.069
P_{16}	36.6912
P_{17}	30.018
P_{18}	42.6504
P_{19}	81.598
P_{20}	30.0049
Total power output (MW)	2513.1
Total transmission loss(MW)	13.1145
Total generation cost ($/h)	**60413.0014**

Table 4.20: Comparison of Total Cost between Various Optimization Techniques

Methods	Reference	Total generation cost ($/h)
GWO	(Wong, Sulaiman, Mohamed, & Hong, 2014)	**60413.0014**
CS	(Basu & Chowdhury, 2013)	60414.10387
FA	(X. S. Yang et al., 2012)	60415
ABCNN	(Karaboga & Ozturk, 2009)	60446.37744
ABC	(Karaboga & Akay, 2009)	60540
BBO	(Bhattacharya & Chattopadhyay, 2010a)	62456.779
LI	(Bhattacharya & Chattopadhyay, 2010a)	62456.6391
HM	(Su & Lin, 2000)	62456.6341
QP	(Bisen & Dubey, 2012)	62456.63
GAMS	(Bisen & Dubey, 2012)	62456.63

4.2.7 Case 7: 38-unit system

A system with 38 generators has been tested. Fuel cost characteristics are quadratic. The input data of the system which shown in Table 4.21 is taken from Sydulu, (1999). The load demand is 6000 MW. Contrary to case 6 which transmission loss has not been considered here.

Table 4.22 shown the performance of GWO with various numbers of search agent and it depicted that 50 numbers of search agents achieved better convergence. At the same time, Figure 4.13 is the convergence curve of various units of search agents with 300 iterations. It shown 50 units of search agents is enough for this system and it converged to optimal solution at last. Therefore, based on the analysis from Table 4.22 and Figure 4.13, 50 numbers of search agents is chosen for this test system due to its better convergence. On the other hand, the proposed method, GWO is executed 15 times for this test system and the performance of GWO per each run is shown in Table 4.23 and Figure 4.14. The worst result obtained for 15 runs is 9420984.257 $/h while the best solution is 9418281.848 $/h. The difference between the best solution and the worst solution is 2702.409 $/h, which is 0.029%. Thus, from Table 4.23 and Figure 4.14, it shows that GWO is stable for each time of simulation and is able to provide each solution approximately near to the optimal solution per run.

The results obtained using proposed GWO has been compared with DE/BBO (Bhattacharya & Chattopadhyay, 2010b), BBO (Bhattacharya & Chattopadhyay, 2010a), PSO_TVAC (K. Chaturvedi, Pandit, & Srivastava, 2009) and NEW_PSO (K. Chaturvedi et al., 2009) are shown in Table 4.24. It is seen that GWO method converges to the solution of 9417433.00 $/hr against 9417235.7863 $/hr for DE/BBO and 9500448.307 $/hr obtained by PSO_TVAC. It shows that GWO has little bit lack behind DE/BBO and placed second out of five optimization techniques. Hence, it testifies to the extraordinary potency of GWO in solving ED problem which is without transmission loss.

Table 4.21: System Data for 38 Generators System without Transmission Loss

Unit	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$	a_i	b_i	c_i
1	220	550	0.3133	796.9	64782
2	220	550	0.3133	796.9	64782
3	200	500	0.3127	795.5	64670
4	200	500	0.3127	795.5	64670
5	200	500	0.3127	795.5	64670
6	200	500	0.3127	795.5	64670
7	200	500	0.3127	795.5	64670
8	200	500	0.3127	795.5	64670
9	114	500	0.7075	915.7	172832
10	114	500	0.7075	915.7	172832
11	114	500	0.7515	884.2	176003
12	114	500	0.7083	884.2	173028
13	110	500	0.4211	1250.1	91340
14	90	365	0.5145	1298.6	63440
15	82	365	0.5691	1298.6	65468
16	120	325	0.5691	1290.8	77282
17	65	315	2.5881	238.1	190928
18	65	315	3.8734	1149.5	285372
19	65	315	3.6842	1269.1	271676
20	120	272	0.4921	696.1	39197
21	120	272	0.5728	660.2	45576
22	110	260	0.3572	803.2	28770
23	80	190	0.9415	818.2	36902
24	10	150	52.123	33.5	105510
25	60	125	1.1421	805.4	22233
26	55	110	2.0275	707.1	30953
27	35	75	3.0744	833.6	17044
28	20	70	16.765	2188.7	81079
29	20	70	26.355	1024.4	124767
30	20	70	30.575	837.1	121915
31	20	70	25.098	1305.2	120780
32	20	60	33.722	716.6	104441
33	25	60	23.915	1633.9	83224
34	18	60	32.562	969.6	111281
35	8	60	18.362	2625.8	64142
36	25	60	23.915	1633.9	103519
37	20	38	8.484	694.7	13547
38	20	38	9.693	655.9	13518

Table 4.22: Performance of GWO with Various Numbers of Search Agent

No. of Search Agent	Total Cost ($/h)
10	9422720.059
20	9424227.123
30	9424072.553
40	9422066.232
50	9419581.142

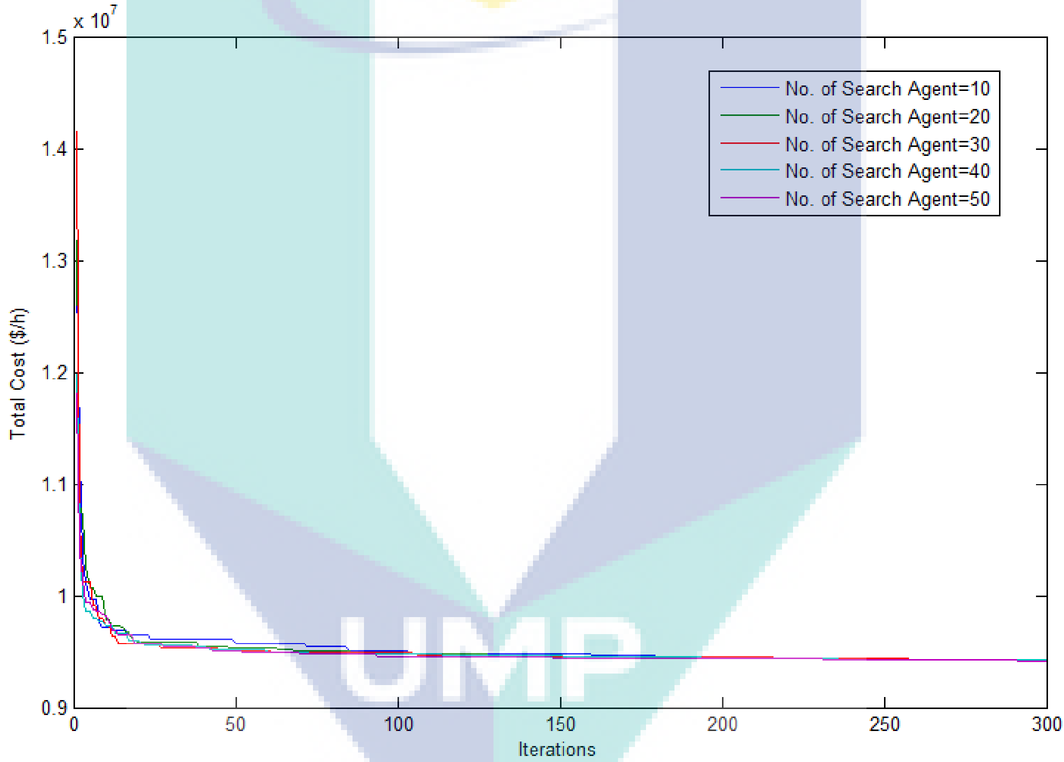

Figure 4.13: Convergence Curve of Various Numbers of Search Agent in 300 Iterations

Table 4.23: Performance of GWO for Each Run by Implementing 50 Search Agents with 1000 Iterations

Runs	Total Cost ($/h)
1	9418281.848
2	9418546.393
3	9419448.493
4	9419031.763
5	9419190.206
6	9418465.42
7	9418667.276
8	9419937.468
9	9418532.419
10	9420984.257
11	9420984.257
12	9418406.113
13	9419720.636
14	9420369.717
15	9419864.546

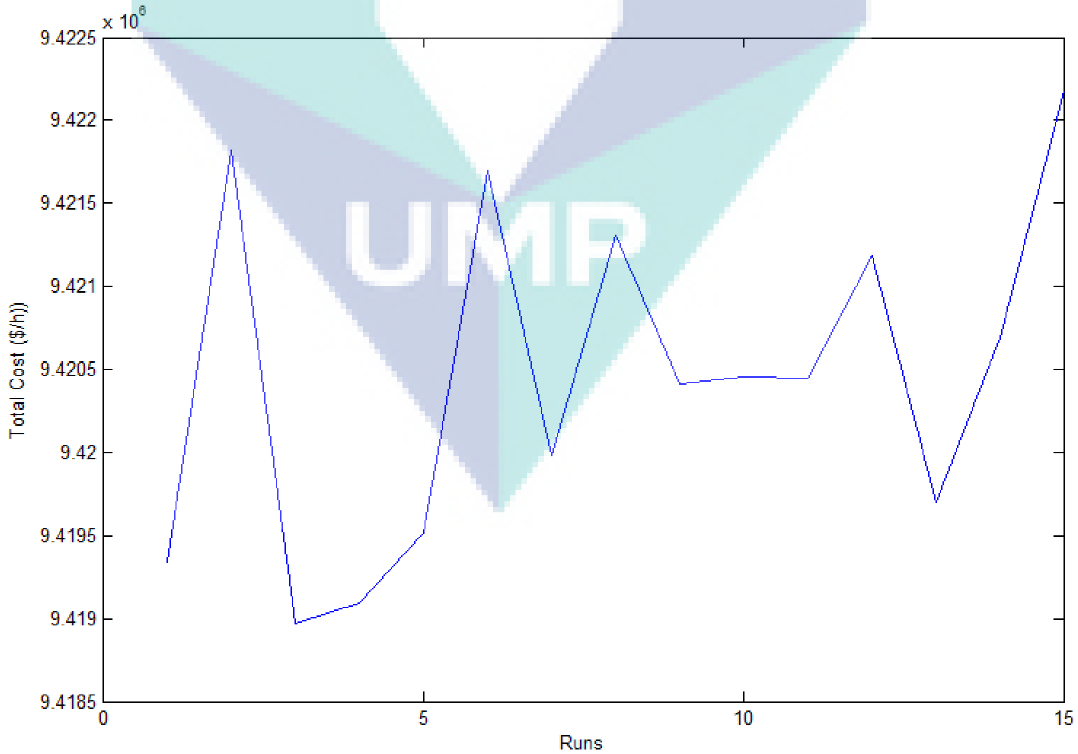

Figure 4.14: Performance of GWO for Each Run by Implementing 50 Search Agents with 15 Runs

Table 4.24: Best Power Output for 38-unit System and P_D = 6000 MW

Unit	DE/BBO	GWO	BB0	PSO-TVAC	NPSO
P_1	426.61	424.79	422.23	443.66	550.00
P_2	426.61	430.70	422.12	342.96	512.26
P_3	429.66	430.70	435.78	433.12	485.73
P_4	429.66	427.62	445.48	500.00	391.08
P_5	429.66	425.87	428.48	410.54	443.85
P_6	429.66	437.33	428.65	492.86	358.40
P_7	429.66	440.42	428.12	409.48	415.73
P_8	429.66	430.00	429.90	446.08	320.82
P_9	114.00	114.09	115.90	119.57	115.35
P_{10}	114.00	114.29	114.12	137.27	204.42
P_{11}	119.77	115.03	115.42	138.93	114.00
P_{12}	127.07	120.44	127.51	155.40	249.20
P_{13}	110.00	110.00	110.00	121.72	118.89
P_{14}	90.00	90.00	90.02	90.92	102.80
P_{15}	82.00	82.00	82.00	97.94	89.04
P_{16}	120.00	120.00	120.04	128.11	120.00
P_{17}	159.60	156.17	160.30	189.11	156.56
P_{18}	65.00	65.00	65.00	65.00	84.27
P_{19}	65.00	65.00	65.00	65.00	65.04
P_{20}	272.00	272.00	272.00	267.42	151.10
P_{21}	272.00	272.00	271.87	221.38	226.34
P_{22}	260.00	259.99	259.73	130.80	209.30
P_{23}	130.65	126.60	125.99	124.27	85.72
P_{24}	10.00	10.03	10.41	11.54	10.00
P_{25}	113.31	115.59	109.42	77.10	60.00
P_{26}	88.07	88.27	89.38	55.02	90.49
P_{27}	37.51	35.73	36.41	75.00	39.67
P_{28}	20.00	20.00	20.01	21.68	20.00
P_{29}	20.00	20.00	20.01	29.83	20.99
P_{30}	20.00	20.00	20.00	20.33	22.81
P_{31}	20.00	20.00	20.00	20.00	20.00
P_{32}	20.00	20.00	20.00	21.84	20.42
P_{33}	25.00	25.00	25.01	25.62	25.00
P_{34}	18.00	18.00	18.02	24.26	21.32
P_{35}	8.00	8.00	8.00	9.67	9.12
P_{36}	25.00	25.00	25.01	25.00	25.18
P_{37}	21.78	22.60	22.00	31.64	20.00
P_{38}	21.06	21.74	20.61	29.94	25.10
Total cost ($/h)	9417235.79	**9417433.00**	9417633.64	9500448.31	9596448.31

4.3 Conclusion

A promising optimization technique GWO is proposed in this chapter to solve the convex and non-convex ED problems. The proposed method shows the potentiality to find the optimum solution so as to minimize the generation cost. The GWO is applied to seven different test cases to assess its performance among 56 optimization techniques. Hereby, GWO is found to be one of the best optimization techniques to solve the ED problem especially in ED problem with ramp rate limits and prohibited zones but less efficient in solving ED problem with valve point loading effects. In conclusion, GWO can be one of the most feasible and prominent solution for solving ED problem alternatively.

CHAPTER 5

OVERALL CONCLUSION

5.1 Summary

In this chapter, the overall conclusion along with the suggestions for future work will be presented. The aim of the research is to incorporate the most reliable optimization technique to solve the ED problem. The ED is a significant problem in order to schedule the power generation among the units in a power system to fulfill the required demand. The main objective of ED problem is to minimize the total generation cost subject to the constraints that have been discussed. In order to show the effectiveness and the feasibility of GWO, seven test cases are used: 3-unit, 6-unit, 13-unit, 15-unit, 20-unit 38-unit and 40-unit systems with different power demands and implemented in linear and nonlinear constraints.

By referring to the results and discussion in Chapter 4, GWO is able to practical alternative for solving economic dispatch problems. This algorithm outperforms in ramp rate limit and prohibited zones of ED problem. The results of this research show that the proposed GWO is able to find very competitive solutions. Hence, this algorithm is considered to be a promising alternative algorithm for solving the ED problems in practical power systems.

5.2 Contributions

The research work that has been presented in this thesis is unique and original contribution to the power system studies especially in power system operation and planning. Numerous of research findings have been documented as publications in peerreviewed journals and conferences. The major contributions of the research are summarized as follows:

i. The introduction of new algorithm, namely GWO in solving different convex and non-convex ED problems has been successfully implemented. It has been observed that the GWO has the ability to provide feasible solutions. Hence, this algorithm can be considered as an alternative way in solving ED problems.

5.3 Areas for Future Research

The validation of applying the proposed method to solve the economic dispatch problem in this thesis gives rise to the number of topics for further research in this area. Some of the recommendations for future research can be summarized as follows:

i. The technique discussed can be implemented by having additional constraint such as valve point loading with multiple fuel options for each unit.
ii. These techniques can be improved as multi-objective optimization techniques for environmental constrained ED problem.
iii. Only thermal generating units have been considered here. The ED problem of hydro units or renewable energy can be implemented by employing this new technique.
iv. Moreover, the proposed algorithms can be applied to other power system optimization problems like unit commitment, optimal power flow, reactive power dispatch and maintenance scheduling.
v. The method can also be extended to solve the dynamic ED problem with more inequality constraints such as transmission limits, voltage limits, prohibited operating zones and spinning reserves.
vi. Hybrid the proposed method to strengthen the robustness of the original technique.

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LIST OF PUBLICATIONS

[1] L. I. Wong, M. H. Sulaiman, M. R. Mohamed, "Solving Economic Dispatch Problems with Practical Constraints Utilizing Grey Wolf Optimizer," *Applied Mechanics and Materials*, Vol. 785 (2015) pp 511-515.

[2] Wong, L. I., Sulaiman, M. H., Mohamed, M. R., & Hong, M. S. (2014, December). Grey Wolf Optimizer for solving economic dispatch problems. In *Power and Energy (PECon), 2014 IEEE International Conference on* (pp. 150-154).

[3] M. S. Hong, M. H. Sulaiman, M. R. Mohamed, L. I. Wong, Comparative Study of Economic Dispatch by Using Various Optimization Techniques, *2014 2nd Power and Energy Conversion Symposium, (PECS)*.

APPENDIX A

8.7	0.43	-4.6	0.36	0.32	-0.7	0.96	-1.6	0.8	-0.1	3.6	0.64	0.8	2.1	1.7	0.8	-3.2	0.7	0.48	-0.7
0.4	8.3	-1	0.22	0.75	-0.3	5.04	1.7	0.54	7.2	-0.3	0.98	-0.5	1.3	0.8	-0.2	0.52	-1.7	0.8	0.2
-4.6	-1	9	-2	0.63	3	1.7	-4.3	3.1	-2	0.7	-0.8	0.9	4.6	-0.3	4.2	0.38	0.7	-2	3.6
0.4	0.22	-2	5.3	0.47	2.62	-2	2.1	0.67	1.8	-0.5	0.92	2.4	7.6	-0.2	0.7	-1	0.86	1.6	0.87
0.3	0.75	0.63	0.47	8.6	-0.8	0.37	0.72	-0.9	0.69	1.8	4.3	-2.8	-0.7	2.3	3.6	0.8	0.2	-3	0.5
-0.7	-0.3	3	2.62	-0.8	11.8	-4.9	0.3	3	-3	0.4	0.78	6.4	2.6	-0.2	2.1	-0.4	2.3	1.6	-2.1
1	5.04	1.7	-2	0.37	-4.9	8.24	-0.9	5.9	-0.6	8.5	-0.8	7.2	4.8	-0.9	-0.1	1.3	0.76	1.9	1.3
-1.6	1.7	-4.3	2.1	0.72	0.3	-0.9	1.2	-1	0.56	1.6	0.8	-0.4	0.2	0.75	-0.6	0.8	-0.3	5.3	0.8
0.8	0.54	3.1	0.67	-0.9	3	5.9	-1	0.93	-0.3	6.5	2.3	2.6	0.6	-0.1	0.23	-0.3	1.5	0.74	0.7
-0.1	7.2	-2	1.8	0.69	-3	-0.6	0.56	-0.3	0.99	-6.6	3.9	2.3	-0.3	2.8	-0.8	0.38	1.9	0.47	-0.26
3.6	-0.3	0.7	-0.5	1.8	0.4	8.5	1.6	6.5	-6.6	11	5.3	-0.6	0.7	1.9	-2.6	0.93	-0.6	3.8	-1.5
0.6	0.98	-0.8	0.92	4.3	0.78	-0.8	0.8	2.3	3.9	5.3	8	0.9	2.1	-0.7	5.7	5.4	1.5	0.7	0.1
0.8	-0.5	0.93	2.4	-2.8	6.4	7.2	-0.4	2.6	2.3	-0.6	0.9	11	0.9	-1	3.6	0.46	-0.9	0.6	1.5
2.1	1.3	4.6	7.6	-0.7	2.6	4.8	0.23	0.58	-0.3	0.7	2.1	0.9	3.8	0.5	-0.7	1.9	2.3	-0.97	0.9
1.7	0.8	-0.3	-0.2	2.3	-0.2	-0.9	0.75	-0.1	2.8	1.9	-0.7	-1	0.5	11	1.9	-0.8	2.6	2.3	-0.1
0.8	-0.2	4.2	0.7	3.6	2.1	-0.1	-0.6	0.23	-0.8	-2.6	5.7	3.6	-0.7	1.9	10.8	2.5	-1.8	0.9	-2.6
-3.2	0.52	0.38	-1	0.8	-0.4	1.3	0.8	-0.3	0.38	0.9	5.4	0.5	1.9	-0.8	2.5	8.7	4.2	-0.3	0.68
0.7	-1.7	0.7	0.86	0.2	2.3	0.76	-0.3	1.5	1.9	-0.6	1.5	-0.9	2.3	2.6	-1.8	4.2	2.2	0.16	-0.3
0.5	0.8	-2	1.6	-3	1.6	1.9	5.3	0.74	0.47	3.8	0.7	0.6	-1	2.3	0.9	-0.3	0.16	7.6	0.69
-0.7	0.2	3.6	0.87	0.5	-2.1	1.3	0.8	0.7	-0.3	-1.5	0.1	1.5	0.9	-0.1	-2.6	0.68	-0.3	0.69	7

B Loss Coefficients for 20-unit System

WONG LO ING MASTER OF ENGINEERING (ELECTRICAL) 2015 UMP