Optimal Distributed Generation Planning Based on NSGA-II and MATPOWER

A thesis submitted for the degree of Doctor of Philosophy

by

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Abstract

The UK and the world are moving away from central energy resource to distributed generation (DG) in order to lower carbon emissions. Renewable energy resources comprise a big percentage of DGs and their optimal integration to the grid is the main attempt of planning/developing projects with in electricity network.

Feasibility and thorough conceptual design studies are required in the planning/development process as most of the electricity networks are designed in a few decades ago, not considering the challenges imposed by DGs. As an example, the issue of voltage rise during steady state condition becomes problematic when large amount of dispersed generation is connected to a distribution network. The efficient transfer of power out or toward the network is not currently an efficient solution due to phase angle difference of each network supplied by DGs. Therefore optimisation algorithms have been developed over the last decade in order to do the planning purpose optimally to alleviate the unwanted effects of DGs.

Robustness of proposed algorithms in the literature has been only partially addressed due to challenges of power system problems such multi-objective nature of them. In this work, the contribution provides a novel platform for optimum integration of distributed generations in power grid in terms of their site and size. The work provides a modified non-sorting genetic algorithm (NSGA) based on MATPOWER (for power flow calculation) in order to find a fast and reliable solution to optimum planning.

The proposed multi-objective planning tool, presents a fast convergence method for the case studies, incorporating the economic and technical aspects of DG planning from the planner’s perspective. The proposed method is novel in terms of power flow constraints handling and can be applied to other energy planning problems.

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Declaration

The work described in this thesis has not been previously submitted for a degree in this or any other university and unless otherwise referenced it is the author's own work.

Statement of Copyright

The copyright of this thesis rests with the author. No parts from it should be published without his prior written consent, and information derived from it should be acknowledged.

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List of Abbreviations

DG	:Distributed Generation
RES	:Renewable Energy Source
CHP	:Combined Heat and Power
DSO	:Distribution Network Operator
MOEA	: Multi-objective Evolutionary Algorithm
GA	:Genetic Algorithm
NSGA	: Non-Sorting Genetic Algorithm
MO	:Multi-objective Optimisation
PGP	:Priority Goal Programming
OPF	:Optimal Power Flow
MOPF	: Multi-objective Optimal Power Flow
SGP	:Sequential Goal Programming
LP	:Linear Programming
NLP	:Nonlinear Programming
SQP	: Successive Quadratic Programming
GRG	:Generalized Reduced Gradient
QP	:Quadratic Programming
IP	: Interior Point Method
MIP	: Mixed-Integer Programming
MINLP	: Mixed Integer Non-Linear Programming
BB	: Branch and Bound
GBD	: Generalized Benders Decomposition
SA	: Simulated Annealing
TS	:Tabu Search
ITS	:Improved Tabu Search
AC	:Ant Colony
PSO	: Particle Swarm Optimization
PV	: Photo Voltaic
SVC	:Static VAR Compensator
VSM	:Voltage Stability Margin
VSI	: Voltage Sensitivity Index
CPF	: Continuation of Power Flow
PLF	:Probabilistic Load Flow
CDF	: Cumulative Density Functions
MCS	:Monte Carlo Simulation
O&M	:Operation and Maintenance

Chapter 1

Introduction

1.1 Background

Accommodating distributed generations (DG) into power system has shown a significant growth over the last decades. The DGs are potentially an attractive source of energy. They don't only provide sustainability and security to power system, but also are a doorway to low carbon technologies such as wind or solar power. UK renewable energy road map report shows that overall, renewable electricity capacity grew by 38% to 19.5 GW in the second quarter of 2013 across the majority of sectors in the UK [213]. The situation of DG penetration in power systems of 15 European member states in 2005 is shown in Figure 1.1 [215].

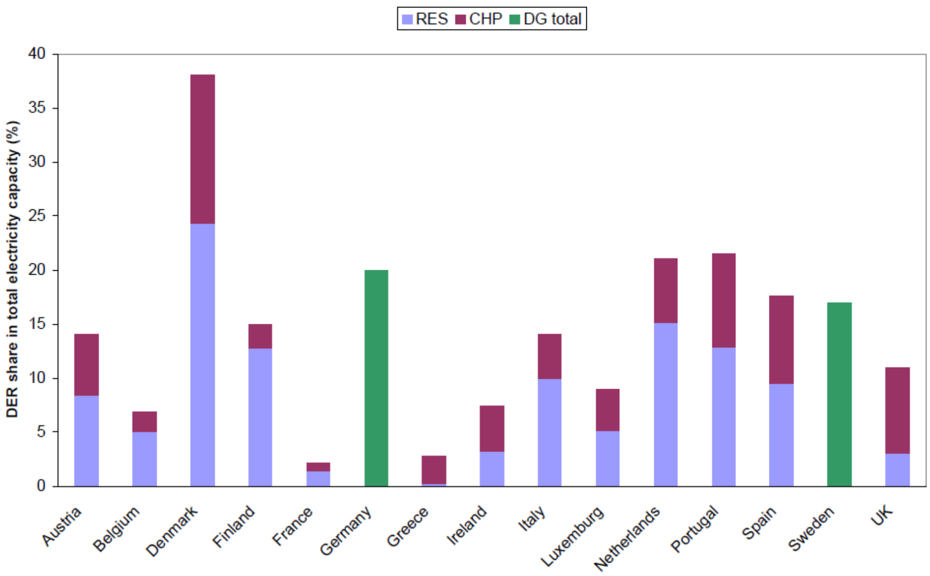

Figure 1.1 DG share of total generation capacity in 2005 [215]

Renewable energy source (RES) and Combined heat and power (CHP) have been represented in different colours but overall, the figure shows that ten countries have a DG capacity above 10%, and half of them are over 20%. The policy objective is 20% integration for the whole European member state in 2020 [215]. Therefore, it could be seen that, the integration of DGs has already begun and rate is obtaining a fast momentum. Any network planner or developers is bound to find the suitable areas and the required capacity for the reinforcement of power network. The reinforcement of network by increasing DG penetration can have an impact on distribution networks system costs. It may lead into extra costs or reduced costs (benefit) for the operator of distribution network (DSO). For example avoiding or delaying the need for costly network upgrades by providing new capacity in the short-term could reduce the investment cost. On the other hand distribution planner has to maximise the profit of the investments for the system development and to improve the performance of the system as well. In many case the goals are conflicting [54]. This is where optimisation techniques are aiding the planner/developers. In publications over decades the problem has been addressed. The most recent techniques show a shift from complex mathematical optimisation techniques to more heuristic techniques to avoid derivates and non-converging outcome [214]. Due to inherent confliction of technical and economic objectives, finding an appropriate balance among sets of conflicting objectives is of interest. The multi-objective evolutionary algorithm (MOEA) optimisation techniques are the ones that provide a frame work for identification of different parameters affecting the technical and cost-orientated objectives, thus an efficient MOEA framework is the one that is adoptable to objectives in a power system and rapid in terms of mathematical calculations. The optimal solution could be varied based on the planner's goals and preferences. Before implementing any sort of optimisation, objectives constraints and scope of the studies should be defined. DG planning objectives are of various types represented in Table 1.1. Table 1.1 could be a longer list but as explained, the objectives vary based on the perspective of network operator. Optimum integration of distribution generations are also based on power flow calculation. Power flows calculation is an indispensable part of optimisation as the all variables are to be recalculated with the new variables.

Table 1.1 Various objectives in DG planning

Technical Objectives	Economic Objectives	Environmental Objectives
Voltage	Cost of equipments	Green house gas emissions
Energy produced	Cost of operation and maintenance of equipment (O&M)	CO_2 emissions
Energy not supplied	Outage cost	Radioactive waste
Energy exported	Cost of energy produced	Noise
Power losses	Revenue	
Line loading	Profit	
Harmonics distortion	Rate of return	
Fault level		
Installed capacity		

1.2 Aim and Objectives

The main aim of the research is to develop an optimisation system that selects the best location and size of DG. In order to achieve this aim, the following objectives are set:

- Develop and test a multi-objective optimisation algorithm based on Pareto ranking and genetic algorithm (GA).
- Develop better optimisation using non-sorting genetic algorithm II (NSGA-II).
- Simulate the electrical system using MATPOWER analysis toolbox [208] as a robust simulation engine.
- Use the optimisation tools with the simulation in selecting the best location and size of distributed generation. The multi-objectiveness is adopted due to the variety of objectives and inherent nature of objectives in optimum integration of power system.

1.3 Contribution to Knowledge

This work represents the first publicly available of NSGA-II- MATPOWER to find the optimum location and size of DGs in terms of the defined objectives. The novelty of the model allows for using any standard case defined in MATPOWER. As constraints such as equality constraints are bases of power flow calculation in MATPOWER, any unfit resolution would be discarded during the optimisation without a need for more than 50 iterations. Therefore the results are obtained in less than a few minutes for hundreds node power system networks. The work also propose a function for shifting the optimum result to a point in which less power flow congestion is imposed on the slack bus hence decreasing the dependency of network from the substation.

1.4 Thesis Outline

Chapter 1 is this introduction which introduces the subject, give aim and objectives, the contributions and the thesis outline.

Chapter 2 review some background material relevant to different optimisations methods with respect to power system in power system networks.

Chapter 3 describes the theory of heuristic and non-heuristic algorithms. In addition it provides a review on some analytical tool used for such algorithms.

Chapter 4 gives details of the system implementation, including the simulation tool, the optimisation algorithm and the interfacing between the package and the optimisation tool which is implemented in Matlab.

Chapter 5 applies the optimisation algorithm to different IEEE standard case systems. The results are obtained for all the systems and the performance is analysed and evaluated with respect to the best results.

Chapter 6 summaries the result of analysis and discuss the further work

Appendix A IEEE 14 bus network data

Appendix B IEEE 30 bus network data

Appendix C IEEE 118 bus network data

1.6 List of Publications

I. Zamani, M. Irving, "A novel approach to distributed energy resource planning using NSGA-II", *in Proc 47th International Universities Power Engineering Conference (UPEC),* 4-7 Sept. 2012

I. Zamani, M. Abbod, M. Irving, "Analysis of decision making in multi-objective DG allocation based on NSGA-II", accepted in 49th International Universities' Power Engineering Conference, 2014

Chapter 2

Literature Review

2.1 Introduction

In this chapter an overview of the current literature on historical evolution of distributed generation and their relative planning methods applied in power system is presented. Technical and mathematical issues on the planning are discussed firstly. Non-linearity in power system is discussed next to illustrate the significance of the optimisation in power system. Optimisation comes with different objectives so in Section 2.5 multi objectiveness is discussed to illustrate how versatile objectives affect the methods used in dealing with multi-objective optimisation. In Section 2.6 an overview of the methods in power system and particularly on distribution generation planning is presented. Methods are divided into two main classes: conventional and heuristic optimisation. Furthermore in this Section the effort has been focused on the relative pros and cons of each technique with respect to its application in power system. In Section 2.7 it has been attempted to show how distribution generation term is perceived in different literature. One of the most important issues in distribution generation planning is the voltage stability. In Section 2.8 its imperative role in power system and different approaches in achieving the stability is presented. Distribution generation planning has also been classed in terms of time scale. In Section 2.9 the effort has been to distinguish the short and long term planning presented in literature. In the last Section of this chapter, the order of optimisation is discussed. The literature illustrates that optimisation is not only diversified by applying different methods, but also by the way that those techniques are applied.

2.2 Evolution in Distributed Generation and Grid Policies

In the recent decade, distributed generation (DG) has been referred as one of the main solutions to address the global warming issue as a large number of DGs are devoid or are of low carbon emissions. Despite strong drivers towards bulk electricity production (centralization), distributed generation facilities constitute a collection of decentralized power production which offer less expensive, more flexible and less environmentally damaging alternatives to traditional utility-owned power plants [1], [2].

The first attempts of increasing DG integration came into existence in 1970s, when fuel costs of fossil fuels skyrocketed as the small scale generation in United States proved economically practical. Consequently more investments on creating incentives to reduce the cost newer technologies resulted in drastic drop in the cost of PV panels and wind turbines [2].

Changes in policy started in late 1990s in United Kingdom and Denmark toward higher integration of distributed generation [3]. In response to that, OFGEM (the office of gas and electricity markets in the UK) implemented regulatory and policy frameworks in early 2000s which do not inhibit the growth of distributed generation. Some of the aims defined in regulation of the UK electricity industry report [4] are as follows:

- Allowing generators the option of spreading the cost of connecting to the distribution network
- Making it easier for domestic combined heat and power (CHP) generators customers with heating systems which can generate electricity to connect to the networks by establishing a standard connections procedure
- Reimbursing distributed generators some of the initial connection fee when another generator connects to the same part of the network, which they have already paid for
- Providing clearer information from distributors on preparation of quotations for connections to the network

- Investigating the best ways to record and meter the amount of electricity that is used against the amount that is put back onto the distribution network by a home with domestic CHP.

Currently, the EU 2020 target of 20% of the EU energy consumption produced from renewable resources is the main motive for the expansion of distributed generation (DG) [5]. The most significant growth in DG technologies is depicted in Figure 2.-1 [5].

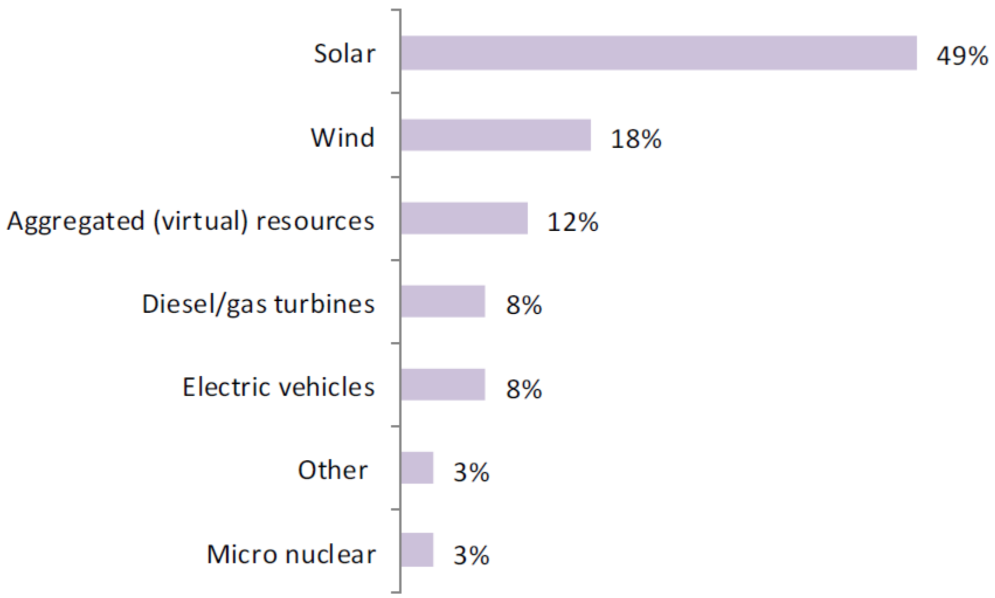

Figure 2.1. Growth of various DG technologies [5]

2.3 Location and Size Issue

2.3.1 Technical Issues

One of the most important characteristic of a power network is power loss. To illustrate the significance of proper size and location a 3D plot versus power loss in a distribution network is depicted in Figure 2.2 [6].

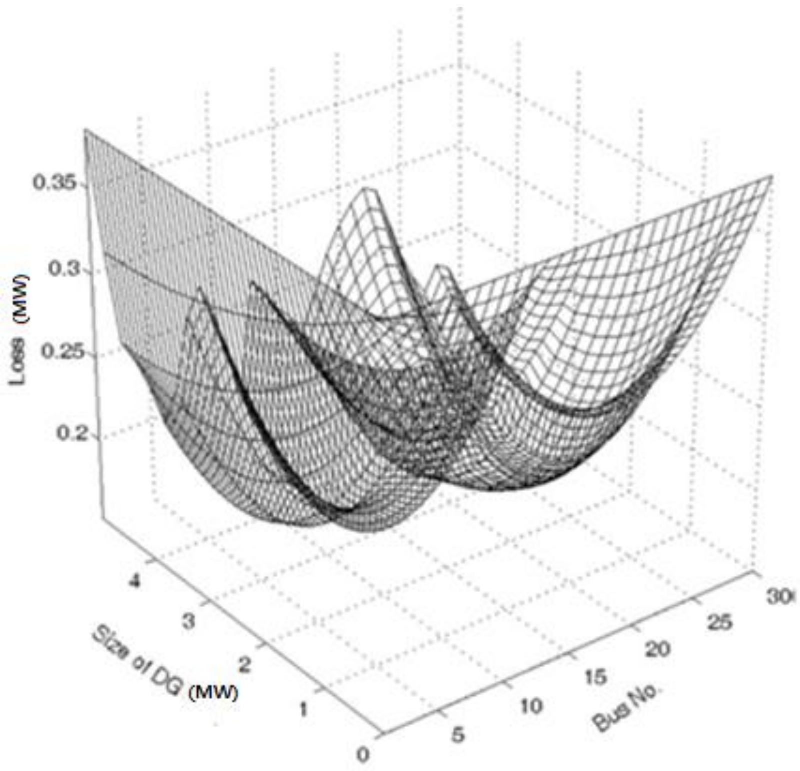

Figure 2.2. Effect of size and location of DG on system loss [6]

From Figure 2.2 it is shown that location of distributed generation (DG) affects the loss. Also for a particular bus, by increasing the capacity of DG losses reduces up to a point and increases again and may exceed the initial losses, hence it is not a good idea to install as high capacity as possible in the network.

The total size of added DG to the network is another dilemma in the optimization as increasing the penetration level of the DGs or maximizing the DG capacity is the main goal so many developers and distribution network operators (DNO) [7]. As a result it could lead to voltage rise or increased fault level. The installation of DG can affect the magnitude, duration, and direction of the fault current so it is required to verify that the change in magnitude, duration and direction of the fault current does not affect the operation of protection devices [11]. In DG sizing and sitting, a horizon of 5-20 years could be considered as part of a long term planning. During these years the structure of network might change because of newly structures such as substations. This dynamicity makes it really difficult to examine all possible network configurations to find the optimal point [12] hence the network structure is assumed to be invariable during the planning period. Another affect of distribution generation is on the direction of power flow. DG will change the power flow in the distribution system, and the distribution system can no longer be considered as a system with unidirectional power flow. So the assumption of unidirectional power flow is no longer valid [61], [62], [63]. It will consequently affect the power distribution system operation and control. Therefore further analyses on impact of added DGs on the distribution systems should be considered.

2.3.2 Exhaustive Calculations Issues

Any single technical issue in Section 2.3.1 such as voltage rise can be approached by heuristic methods described in Section 2.6.2. Such methods are computationally exhaustive which search the space corresponding to the locations and capacities of DG plants that could be connected to a distribution network. However, the actual benefit brought by exhaustive analyses is that a number of technical issues and constraints could be included. Although exhaustive methods applied to a connection evaluated for a certain demand and generation scenario is not necessarily computationally intensive, this is not the case when multiple connections and the variability of demand and generation are considered, increasing considerably the computational burden of the exhaustive analysis [14].

2.4 Non-linearity in Power System

Solution techniques for DG optimal allocation are interpreted as a mixed integer nonlinear optimization problem. Usually, it includes maximizing the system voltages or minimizing power loss and cost. The solution criteria vary from one application to another. Therefore, as more objectives and constraints are considered in the algorithm, more data is required, which adds difficulty to non-linearity of implementation [13]. In some optimization techniques such as loss sensitivity factor, where some of the buses are not taking into account, the optimum point might be missed. Figure 2.3 illustrates this notion [6].

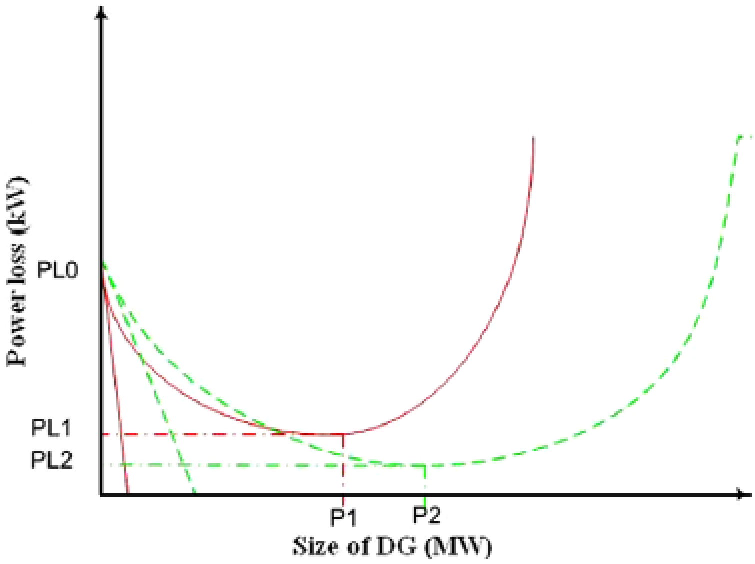

Figure 2.3 Non-linearity in loss curve [6]

2.5 Multi-Objectiveness

Single objective optimization yields optimal solutions of a single aspect which may not be acceptable to the utilities [107]. Therefore, multi-objective approaches are required to solve the problem [9], [10]. The use of Multi-objective optimisation (MO) techniques has a number of advantages. It allows the management of different objectives and makes it easier to take a decision in the end or before running the optimisation based on the view that system operator takes [8]. On the other hand multiple objectives might not be optimized simultaneously because of innate conflicts existing between them [104]. To tackle this problem there is generally three approaches to consider multi-objectiveness.

2.5.1 Priority Goal Programming

This approach is built on the conventional techniques for generating trade-off surfaces. The objectives are aggregated into a single parameterized objective function and trade offs are determined based on the weighting coefficients values [104]. In the publication of Nangia *et al.* [10], weighting method is used to aggregate cost of generation function and system transmission losses to study the co-relation between each objective and its weight factor in an optimal power flow problem. In the work of Yun *et al.* [106], authors solved a voltage control problem by an extension of the simplex known as goal programming simplex by ranking the priority of the control objectives. Several objectives such as adjusting reactive power of generators are considered to increase the reliability and stability operation of a power system. In the publication of Abou El-Ela *et al.* [103] weighting factors are applied to obtain overall maximal composite benefits of added DGs. Priority goal programming is an easy and efficient approach to implement but requires extensive sensitivity analysis if prior assessment of weights is going to be used [10].

2.5.2 Sequential Achieving Objectives Programming

In this approach one objective function is selected as master objective function. This is generally an objectives which is considered most important and it is minimized first [107]. The other objective functions are considered as slave which are added to other constraints. Then the master objective function is released, within a certain boundary, to optimize another slave objective function [104]. The process is repeated till all the objectives have been considered. In the work of Nangia *et al.* [107], a multi-objective optimal power flow (MOPF) problem is solved by sequential Goal Programming (SGP). Generation, system transmission losses, environmental pollution are considered in 6 different scenarios based on the order or objective minimisation. The final solution is decided based on regret analysis.

2.5.3 Pareto-Based Multi-Objective Algorithms

In Pareto based multi-objective programming there is no single optimal solution that simultaneously optimises all the objective functions so in some literature it is referred to as non-deterministic approach [179]. In such cases, the decision makers are looking for the most desirable solution. In this method the concept of optimality is substitute with Pareto optimality [177]. In Pareto-based multi-objective algorithms all objectives are optimised at the same time and solutions which are not dominated by another solution are chosen and illustrated in an n-dimensional space as n represents the number of objectives. In other words in this methods multi-objective problem is directly addressed through the use of separate objectives and produce an optimum set of points (Pareto frontier) [178].

2.6 Non-Heuristic and Heuristic Optimization

The optimal integration of renewable has been done by various methods. Different formulations have been solved using calculus-based methods, search-based methods and combinations of these techniques. The calculus-based methods such as linear programming are classes as non-heuristic. These optimisation methods treat the DG capacities as continuous variables while their locations remain fixed [15]. This Section presents a review of the various methods employed to date. They are categorized into two main category heuristic (conventional) and non-heuristic optimization.

2.6.1 Non-Heuristic

Non heuristic are also called conventional, classical or derivate-based optimisation. To search for the optimal solution in this class techniques such as gradient operators in a single path search are used [96]. Non-heuristic algorithms could be such as linear and non-linear programming, quadratic programming and interior-point methods.

2.6.1.1 Linear Programming

Linear programming (LP) problems are problems with a linear objective function, linear constraints and continuous decisions variables [16]. The term “linear” means all the mathematical relationship among the variables are devoid of non-linearity [17]. Fundamentally, linearization applied on power flow or the results from an ac power flow generates an error, but it is not a significant one in the context of discrete distribution generation capacity [14]. In the publication of Liew and Strbac [100], an optimal power flow (OPF) was developed based on linear programming to investigate the potential benefits and cost of connected embedded wind generation. The developed OPF minimises the annual active generation curtailment cost within power, voltage and thermal constraints. In the work of Khodr *et. al* [101], another linear branch and bound mathematical model was presented to minimize the sum of investment costs, fuel costs, operation and maintenance costs, and unavailability costs. The optimisation gives the optimum number of units, size of DGs and their and type. In the publication of Keane and O’Malley [102], a new methodology is developed using linear programming to find the suitable locations and size for DG on distribution networks. In this method individual voltage sensitivity characteristics are employed to characterize constraints, such as voltage, thermal and short circuit limits. In the work of Abou El-Ela *et al.* [103], linear programming (LP) is used to investigate the influences of varying ratings and locations of DG on the objective functions to maximize the weighted factor benefits of DGs. It is done by choosing the optimal sitting and sizing of DG with respect to system constraints. The literature showed advantages and disadvantages of LP applied in power system. It is reliable, especially about convergence properties. It is also quick in identifying infeasibilities. Another advantage of LP is its capability to accommodate a large number of power system operating limits. Nevertheless, despite all the advantages, it lacks accuracy as opposed to more accurate nonlinear power system model [18].

2.6.1.2 Nonlinear Programming

The term nonlinear in nonlinear programming (NLP) refers to fact that computation is based on the derivates. The first step in this method is to choose a search direction in the iterative procedure. The direction is set by the first partial derivatives of the equations hence; these methods are referred to as the first-order methods such as generalized reduced gradient (GRG). The successive quadratic programming (SQP) and Newton's method require the computation of the second-order partial derivatives of the power-flow equations and other constraints (the Hessian) and are therefore called second-order methods [18]. In the work of Rau and Yih-Heui [109], the proposed second order algorithm is preferred over reduced gradient as the reduced gradient method fails to converge for positive injections .The second order algorithm computes the capacity of DGs in selected nodes to maximise the benefits of distributed generation expressed as an index of performance. In the publication of Ramos *et al.* [110], a non-linear programming solution was adopted to obtain the optimal generation planning by deriving objective functions such as the deterministic cost model. NLP methods have higher accuracy than LP and the convergence does not depend on the starting point [111]. However, when NLP is applied in large power system problems the disadvantages emerge. The main drawbacks is that NLP is not capable of satisfactorily handling non-convexities and non-smoothness such as generator's prohibited operating zones, operating constraints of the transmission lines such as thermal limits and switchable VAR source constraints [40]. The second downfall is its slow convergent rate. It could be due to a zigzagging in the search direction. Furthermore, in NLP, different optimal solutions are depended on the starting point of the solution because the method can only find a local optimal solution [18].

2.6.1.3 Quadratic Programming

Quadratic programming (QP) is generally considered as subset of nonlinear programming. The name "quadratic" refers to the quadratic form of objectives

[111]. In the work of Finardi *et al.* [112], authors used a sequential quadratic programming algorithm to solve a unit commitment problem due to non-linear nature of sub problems resulting from decomposition. Lavei *et al.* [113] utilised quadratic optimisation for power flow optimisation to tackle the high non-linearity of constraints.

2.6.1.4 Newton Methods

The second order partial derivates of power flow equations is required for this method. The Newton approach was brought to the attention in the publication of Sun *et al.* [114] as a tool for obtaining the optimal power flow. In literature application of the Newton method in OPF problems have been popular [49], [109]. Newton method is simple and efficient in equality constraints handling and very popular in optimal power flow problems, because it is simple in treating inequality constraints [115]. However, this method lacks the ability of searching global optimum and easily traps in local optima in optimal planning of the DG problem. Distribution of distributed generation problem has severe non-linearity due to the physical constraints such as balance between power supply and demand, limitation for the total dispersed generation injection capacity [49].

2.6.1.5 Interior Point Method

Interior point methods (IP) were originally applied in OPF problems. Although this method was used for solving linear problems, it was extended later for QP and NLP forms [111], [123]. IP has been used for several power engineering optimization problems, including state estimation [116] optimal power flow [117], [118], [119], [120], hydro-thermal coordination [121], [122], voltage collapse and reliability evaluation [123], [124], and fuel planning [125]. In the work of Grenville *et al.* [123] the insolvability issue was rectified by applying interior point model to unsolvable states in an optimal power flow case. One of the drawbacks of IP methods is their difficulty in finding infeasibility. The computation of each iteration of an IP algorithm is dominated by the solution of large linear systems; therefore, the performance of any IP code is highly dependent on the linear algebra [117].

2.6.1.6 Mixed-Integer Programming

Mixed-integer programming (MIP) optimization represents a powerful framework for mathematically modelling power system problems that involve discrete and continuous variables [20]. Variables such as transformer tap ratio, phase shifter angle and unit on or off status could be defined as discrete variables [111]. A mixed integer non-linear programming problems (MINLP) variables with values of 0 or 1 represent whether a new DG source should be installed [18] so decision variables can only take integer values. It is usually used when fractional units are not an option like the number of positional DGs. When some of the variables are continuous, the problem is mixed-integer. Different methods that have addressed the solution of MINLP include the branch and bound method (BB) [18] and generalized benders decomposition (GBD). Branch and bound method (BB) is used for integer programming [18], [20]. The BB method is generally only attractive if the NLP problems are relatively inexpensive to solve, or when only few of them need to be solved. This could be either because of the low dimensionality of the discrete variables or because the internality gap of the continuous NLP relaxation is small [20]. General benders decomposition (GBD) is another method used to solve nonlinear mixed integer problems. In this method, the problem is divided into a master (integer or mixed integer) and slave problem (nonlinear programming) which are solved independently [21]. GBD applied in the publications of Gomez *et al.* [22] and Granville *et al.* [23] show improvement in the efficiency in solving a large-scale network by reducing the dimensions of the individual sub problems. The results illustrate a prominent reduction of the number of iterations, computation time, and memory usage. Also, decomposition allows the application of a separate method for the solution of each sub problem, which makes the approach very attractive [111].

2.6.2 Heuristic Methods

Mathematical models of optimisation problems may become so complex as the size of power system network expands so that conventional optimisation techniques presented in Section 2.6.1 methods and other deterministic techniques might not be applicable to them. Alternatively, a new class of optimization techniques called as heuristics is applied for the solution. The term heuristic is linked to algorithms mimicking some behaviour in nature, e.g., the principle of evolution through selection and mutation (genetic algorithms or the self organization of ant colonies (ant colony optimization) [24].

- Properties of Heuristic Algorithms

A heuristic should be capable of providing high quality (stochastic) approximations to the global optimum. A well behaved heuristic is robust to changes in problem characteristics. It means the whole class of the problem should be addressed not a single problem. Another important property of such algorithms is that despite of its name, a heuristic might be stochastic, does not contain subjective elements [24].

- Classification of Heuristics

The most popular way to classify heuristic algorithms is based on trajectory methods and population-based methods. The objective in trajectory method is to find efficient neighbourhood functions that give high quality local optima [24]. The iterative techniques applied in this optimization avoid the program to fall into local optima. On the other hand population-based heuristics use a population of solutions which evolve during a certain number of iterations, returning a population of solutions when the stop condition is fulfilled [25]. Therefore population based is more efficient in terms of searching the whole space but it comes at the cost of more computational operations [24]. Table 2.1 shows some example of heuristic classed into two categories.

Table 2.1 Heuristic optimisations [25]

Trajectory Heuristic	Population Based Heuristic
Simulated Annealing	Genetic Algorithm
Threshold Accepting	Differential Evolution
Tabu Search	Ant colony
Hill Climbing	Particle Swarm Optimisation
Greedy randomized adaptive search procedures	Scatter search
Variable neighbourhood search	Path re-linking
Iterated local search	Artificial bee colony optimization

2.6.2.1 Simulated Annealing

Simulated annealing (SA) is based on an analogy between combinatorial optimization and the annealing process of solids. Similar to the classical local search an improvement of the solution for a move from a solution to a neighbour solution is always accepted. Simulated annealing minimizes numerical functions of a large number of variables. Moreover, the algorithm accepts also a move uphill, but only with a given probability. Random uphill jumps provide escapes from local energy wells. Therefore, it converges asymptotically to the global optimal solution with probability one [18]. The SA method was originally proposed to solve the unit commitment problem [126] and proved highly robust in handling unit commitment constraints. Further SA-based algorithms were applied to network tearing [128], maintenance scheduling [129], capacitor placement [130], distribution planning [131] and economic dispatch problem [132]. In 1994 a SA method was proposed by Wong and Wong [127] to determine the optimum hydrothermal short-term schedule which showed worst schedule found by this algorithm is very close to the exact solution (only 0.118% higher than that found by the gradient method). A comprehensive approach to strategic planning of VAR compensators in a non-sinusoidal distribution system was presented by Chu *et al.* [133]. The algorithm is based on simulated annealing to determine the optimal locations, types and sizes, and settings of VAR compensators. SA employed by Chu *et al.* [133] shows how SA allows the modelling can be done on realistic (discrete) rather than continuous values. In the work done by Billinton and Jonnavithula [134], simulated annealing is proposed to determine the number and location of switches as a combinatorial non-linear, non-differentiable optimisation problem considering investment, operation, maintenance, and outage costs. The solution to the problem is proved suitable for large scale distribution systems. Similarly, Jiang and Baldick [135] used SA to optimise switch configuration of a distribution system. Due to the well behaved characteristic of SA for a large combinatorial optimization problem, it was adopted for loss minimization in the work of Jeon *et al.* [136]. SA approach managed to avoid local minima by expanding the cost function by adding the operating conditions of a distribution system. Test results confirmed the robustness of the proposed approach. The optimization method presented by Nahman and Peric [137], adopts the SA for a search within the graph consisting of all line routes of a newly planned network. The initial feasible minimum cost solution is determined by applying a steepest descent approach. This solution is a modified step by step SA searching for the minimum total cost solution using simulated annealing technique to search for the minimum total cost solution including the customer cost caused by load. The algorithm efficiently produced a feasible solution that was very close to the optimal solution.

2.6.2.2 Tabu Search

The term Tabu Search (TS) was first used in 1986 by Glover [138]. Tabu search is particularly designed for finite discrete search spaces. It is an iterative search method which uses a search algorithm at each iteration to find the best solution in some subset of the neighbourhood, generated from the best solution obtained at the last iteration [139]. Choosing neighbourhood is done in a way to avoid cycling, i.e. finding the same solution more than once [24].Therefore it can achieve an optimal or suboptimal solution within a reasonably short time and reduce on the number of iteration. Fundamentally this efficiency is achieved by employing a short term memory, known as the Tabu list .This list contains of recent visited solutions [24]. In the publication of Abido [140], TS algorithm was proposed to solve the OPF problem. It was shown that unlike the traditional optimization techniques, TS can easily deal with non-convexity of objective functions regardless of a starting point, giving a lesser cost compared to the evolutionary programming. TS approaches have also been proposed for the unit commitment problems [141], [142], [143]. In the work of Borghetti *et al.* [141] even a straightforward implementation of TS proved to give good results in a short computing time. Tabu search was also proposed for feeder reconfiguration in the publication of Mori and Yogita [145], in a parallel approach to reduce computational efforts and accuracy. Similarly in the work of Li *et al.* [146], TS algorithm was used for another network reconfiguration problem in order to reduce the resistive line losses under normal operating condition. TS has been modified to become a more viable solution in power system optimisation problems. For instance in the publication of Purushothama and Jenkins [147], a combined SA and TS approach was used to solve the unit commitment to extend the stochastic neighbourhood algorithm. The same hybrid combination was used by Jeon and Kim [148] to improve the computation time and convergence property in a feeder reconfiguration problem. Other TS hybrid methods are such as modified Tabu search (MTS) [149] and improved Tabu search (ITS) [150]. In the latter loss minimization reconfiguration in large-scale distribution systems was achieved by ITS.

2.6.2.3 Ant Colony

Ant colony (AC) was first introduced in 1992 [27], [28]. It is inspired from ants’ movement for food. First an ant explores its neighbourhood randomly. Trace of pheromone on the ground which will guide other ants to the food. Pheromone traces are defined based on the quantity and quality of the food affecting the intensity of it [24]. The AC algorithm was first implemented for the TSP. The TSP is the problem of finding minimum cost of travelling to a finite number of cities along with the cost of travel between each pair of them and returning to the starting point [154]. Ant Colony algorithms have recently been used in power system problems as powerful tools to solve problems such as optimal reconfiguration of distribution systems [29], optimal placement of capacitors in distribution systems [30], scheduling problems including the unit commitment and economic dispatch problems [31], [32], [33], optimum switch relocation, network reconfiguration problems for distribution systems [34], [35], [36] and planning problems [37], [38], [39]. In the work of Gomez *et al.* [152] the AC is defined at the optimization layer and combined with a distribution system load-flow algorithm to solve the primary distribution system planning problem. It calculates the location and the characteristics of the circuits with regard to minimizing the investment an operation costs. In the publication of Alvarado *et al.* [151], an improved version of the ant system algorithm was adopted in a distribution planning problem. The objective function of the problem was defined as the sum of the total costs, considering the fixed and operational loss costs. The results show an improvement compared to the original AC. In the work of Ippolito *et al.* [154] authors used AC for the planning of electrical distribution systems expansion. The results demonstrated that AC is more robust than SA with higher quality because it has a lower standard deviation.

2.6.2.4 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is another population based optimization method proposed by Eberhart and Kennedy [41]. It is a computational intelligence-based technique introduced for continuous functions. PSO is not largely affected by the size and nonlinearity of the problem, and is efficient in terms of convergence in many problems. Therefore it can be effectively applied to different optimization problems in power systems [47]. Advantages of PSO could be summarized as follows:

- Number of parameters are limited so adjusting them is easier
- It has more effective memory capability than genetic algorithm because, every particle remembers its own previous best value as well as the neighbourhood best
- PSO is more efficient in maintaining the diversity of the swarm .It is because each particle gets passive additional information from

another particle that is selected at random. This could enhance the diversity of the swarm [42]

The first applications of PSO were only capable of handling nonlinear continuous optimization problems. By further development of this technique its capability to handle a wide class of complex problems increased [156], [157]. One of the first publication on PSO in power system appeared in the work of Gilli and Winker [24]. PSO was used to minimize the real power losses of an electric power grid. Later on, similar problems were addressed in the works of Yoshida *et al.* [159], [161] and Fukuyama and Yoshida [160] by following the trend. Since power flow calculations involve solving a system of nonlinear equations, PSO technique demonstrated effectiveness in solving this difficult optimization [155] hence it has been applied in economic dispatch [162], [163], [164], reactive power control [158], [159], [161], [165], [166], optimal power flow [167], [168], [169], power system controller designs [170], [171], [172] and feeder reconfiguration problem [173], [174]. PSO has also been applied to many DG planning problems. In the publication of Kuersuk and Ongsakul [43], the PSO method was implemented to obtain optimal location and sizes of DGs. In the work of Kai Zou *et al.* [44], the technique was implemented to design a new optimization framework for distribution system planning. It is based on the integration of ordinal optimization [15] with tribe PSO. In tribe PSO, the particles, informers, and tribes are three basic elements. The informer is a particle, which passes useful information to other particles. The tribe is a group of particles that share the information with each other [44]. In the publication of Kannan et al. [175], PSO was employed to minimize the total cost of the generation expansion planning problem. In the similar problem PSO was adopted in solving the expansion planning problem of a transmission line network in the work of Sensarma *et al.* [176].

2.6.2.5 Genetic Algorithm

Genetic algorithm (GA) is an artificial intelligence technique for optimization developed in 1970s by John Holland. Similar to other population based heuristic techniques it is based on natural selection such as mutation, and crossover [46]. The first application of GA in power system was done in 1990s on reactive power dispatch problem by Iba in 1994 [48]. Later on in some other publications [11], [45] the solution of DG allocation using GA was investigated [11], [45]. Efficiently solving the optimal sitting and sizing of distributed generators through GA was illustrated in the publication of Silversti and Buonaao [45]. In the work of Popovic *et al.* [50], a GA methodology for optimizing and coordinating the placement of distributed generators in a distribution network was introduced in order to enhance the reliability of the system. It is evident that the optimal integration problem of distributed energy resources in the distribution system by GA has been used often in the literature. In some literature GA has been preferred over other heuristic as it is inherently suited to solve location problems [14], [52], [53].

GA is also combined with other techniques for the optimum results. For instance in the publication of Kim *et al.* [49], conventional GA with improved genetic operators was introduced to obtain a better search solution in optimal distribution of dispersed generation where as Harrison combined GA with optimal power flow to provide a means of finding the best locations within a distribution network [51]. One of the frequently used combination of GA is with ε-constrained [53], [54] as far as the optimisation is defined by one object functions [14]. However, combining objectives into one objective in power system problems requires a strong knowledge of exploring space [14] so GA has also been evolved into another form in recent years named as non sorting genetic algorithm (NSGA) introduced by Deb [55]. In Chapter three this method will be discussed more.

2.7 Distribution Generation Types

Distributed generation (DG) provides electric power in the power system. It is featured by characteristics such as small size, compact, and clean electric power generating units which are located at or near an electrical load (customer) [56]. However some DGs such as compound heat and power (CHP) are not completely clean and are referred as traditional DG in some literature. On the other hand in the second category fall more modern DGs such as PV or wind turbine which are completely environmentally friendly. From the technical point of view, DGs are classed into different types based on the injection type or their capacity.

2.7.1 DG Injection Model

There are four type of DG in terms of the power they provide to the system. The first type is only capable of supplying only real power. Certain type of DGs like photovoltaic (PV) will produce real power only [58]. Therefore PV systems are designed to operate at unity power factor. This design benefits residential customer, since they are billed only for the active power that they consume .It is also possible that PV systems may be operated at non-unity power factor but it is due to the utility regulations approval [59].

The second type of DG is those which are capable of supplying only reactive power. Devices such as synchronous condensers and SVCs are as such. Induction generators in wind turbines supply real power but consuming reactive power so they are in the third group. The reactive power consumption consist of the magnetizing current, proportional to the square of the voltage, and the reactive power losses in the leakage reactance, proportional to the square of the current [60] . The forth group is capable of providing both real and reactive power injection, such as synchronous generators. Therefore, the use of DGs utilizing overexcited synchronous generators will allow on-site production of reactive power [76]. Synchronous generators are widely used for steam and combustion engine driven plants such as Combined Heat and Power (CHP) plants.

2.7.2 DG Sizes

According to [57] DGs can also be defined in terms of their capacity. There is a consensus that DG capacity cannot exceed 100-150 mW due to the technical constraints, so they are divided into four size types:

- Micro distributed generation: 1 Watt < 5 kW
- Small distributed generation: 5 kW < 5 mW

- Medium distributed generation: 5 mW < 50 mW
- Large distributed generation : 50 mW < 150 mW

As an example micro-turbines are classes as small distributed generation. Their scale is 0.4–1 m^3 in volume [56].

2.8 Voltage Stability in Power System

Integration of DGs brings about the steady-state and the dynamics of the distribution system. These impacts were discussed in Section 2.3.2. However, voltage instability problem in a network is one of the most harmful disturbances on power system. As of Section 2.7.1 most DGs cannot produce reactive power. Thus, they cannot support voltage stability during dynamic state. Therefore, it is necessary to consider voltage stability constraints for planning and operation of distribution systems [67]. Voltage stability has become rather important in modern power systems, as systems are being operated close to their security limits [64]. That is why in distributed generation planning voltage stability has been one of key issue to address [66]. Voltage stability is to do with ability of the system to keep the voltage magnitude while transporting active and reactive powers. There are two types of voltage stability. Short-term (transient), which is up to a few seconds and long-term (steady state) voltage stability at timescales up to several minutes. In optimisation most of the discussion is about long-term voltage stability. It is useful for indicating the possible voltage collapse, where the term voltage collapse refers to the situation where the system is no longer able to maintain the voltage [65]. Dynamic analysis is becomes more significant when a better understanding of voltage stability phenomena is required [68]. In DG planning a voltage-stability index was introduced in 2001 to search for the most sensitive buses to voltage collapse in radial networks [69]. Bus indices for considering the effect of aggregated DGs into the voltage security of a transmission grid are developed in [71] based on the voltage stability margin (VSM) which is based on P-V curve concept. The P-V concept will be discussed in the next Section 2.8.1. In order to determine the most suitable sites for DGs a voltage sensitivity based approach related is proposed. Voltage sensitivity index (VSI) is used to identify and rank the nodes within the network with respect to receiving new generation. It is assumed that generators can connect to any point in the network subject to security constraints and are not restricted in their location by generator controllers or existing protection devices [50].

2.8.1 P-V Analysis

PV analysis is a widely graphical used tool, in analysis of voltage stability in power system. The active power (P) can either represent the total active power load in an area or the power flow across an interconnection between two areas and the state variable (V) is the voltage at a certain bus. The P-V curve is obtained by increasing the load demand and solving the new power flow. Figure 2.4 from [76] shows the impact of a DG on voltage stability of a bus.

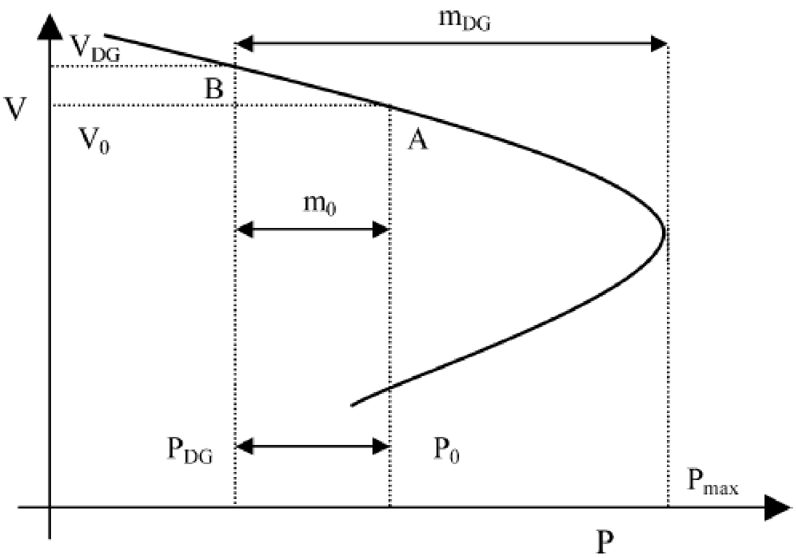

Figure 2.4 P-V curve enlargement of voltage stability margin [76]

As illustrated by instillation of a DG unit moves the operation point from point A to point B on the associated P-V curve, which results in an increase of the node voltage and enhancement in voltage security. The stability margin increases from m_0 to m_{DG} [76].

2.8.2 Continuation of Power Flow

In some literatures optimum location of DG units in distribution networks is based on the analysis of power-flow continuation [77]. After that, the DG units with certain capacity will be installed in these buses via an objective function and an iterative algorithm. In this algorithm, continuation power-flow method is used for determination of the voltage collapse point or maximum loading. Voltage stability analyses can be assessed by obtaining voltage profiles of critical buses as a function of their loading conditions. PV curves provide valuable information about the system's behaviour in different load level .It has been used by the electric power industry for assessing voltage stability margins and the areas prone to voltage collapse [75].

2.8.3 Modal Analysis

Modal analysis was proposed by Gao [72]. It can discover the instability characteristics and can be used to find the best sites for reactive power compensation, generator re-dispatch, and load-shedding programs [70]. Modal analysis involves calculation of Eigen values and eigenvectors of the power flow Jacobian [73]. Using these values near the point of voltage collapse identifies vulnerable buses to voltage collapse. It also gives information about the loads responsible for voltage collapse. Unlike continuation of power flow, when a modal analysis is used; there is no need to drive the system to its maximum stress level [74].

2.9 Planning

DG planning in general consists of justifying the allocation patterns of energy resources and services, formulation of local policies regarding energy consumption, economic development and energy structure, and analysis of interactions among economic cost, system reliability and energy-supply security [25]. Planning in this thesis however is restricted to DG optimal integration which is defined in structured approach to optimise the location, number and size of distributed resources. In the literature planning is viewed as two types: short-term and long-term planning.

2.8.1 Short-Term Planning

The purpose of short-term planning is to make sure that system can continue to serve customer load while meeting all standard. The product of short-term process is series of decisions made for the allocation of distribution generation in the lead time. As an example the lead time could be four meaning that decision is made four years before implementation [78]. Short-term load forecasts are required for the control and scheduling of power systems [79]. This is illustrated in Figure 2.5. The result is different projects in terms of required any ancillary services or a source of active or reactive power to the network. In addition, sometimes it is required to install some voltage regulator or change the transformers tap within the network to compensate voltage drop and to have a smooth voltage profile.

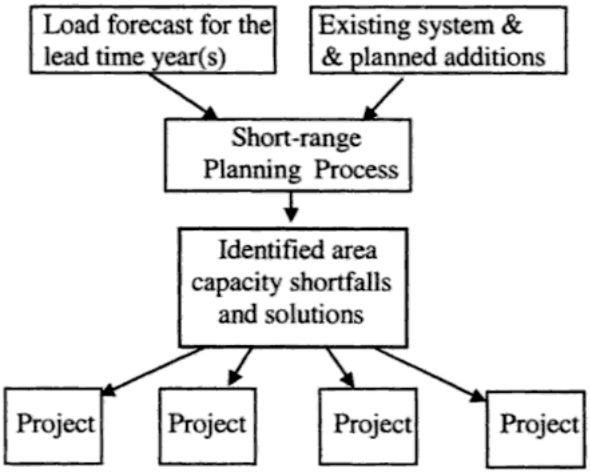

Figure 2.5 The short term planning process [78]

2.9.2 Long-Term Planning

Similar to short-term planning, the long-term DG planning has the objective of determining the least-cost expansion plan which ensures a reliable supply to the future electricity demand. The reliability issue is concerned with an adequate energy supply even under adverse conditions, which are uncertain [82]. Unlike short-term planning, long-term planning product is not a decision, but a long range plan [80]. Major events could affect the power system network in a long period meaning that the existing uncertainty should be considered. The possible projects are not necessarily going to be implemented. As illustrated in Figure 2.6 a multi-scenario assures that short-term decision fits various long range situations.

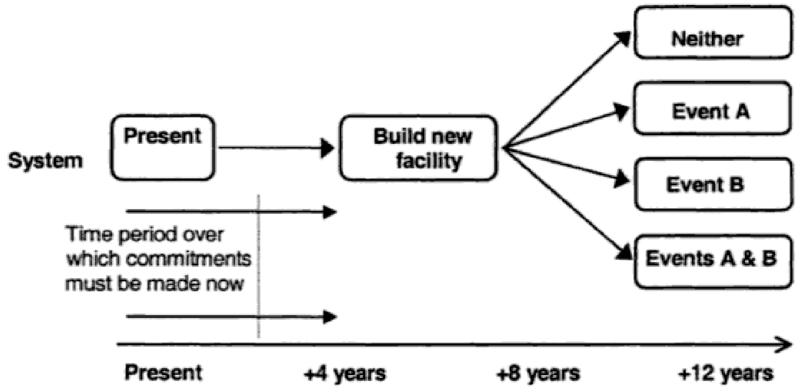

Figure 2.6 The long-term planning process [80]

Uncertainties in power system have various many types. The main sources of uncertainties include the uncertain fuel prices, demand growth, and equipment outages [83]. To deal with the load uncertainties load duration curve was introduced in [97]. It is a simple model which describes the total time through a certain period. The demand is described over a certain period shown in Figure 2.7.

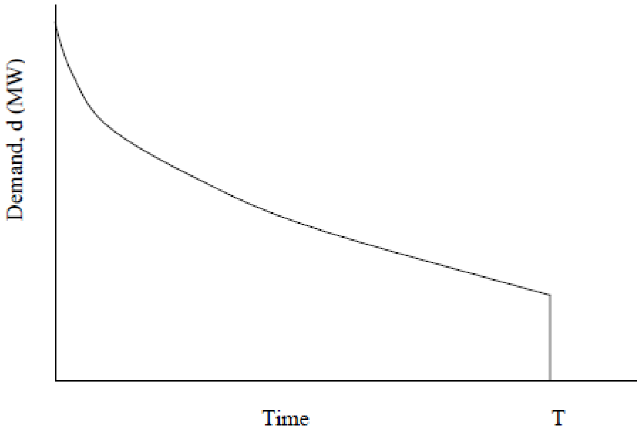

Figure 2.7 Load duration curve [99]

The load duration curve can be approximated by a piecewise constant curve with k segments as shown in Figure 2.8. The downside of this model is that doesn't consider technical restrictions and stochastic fluctuations.

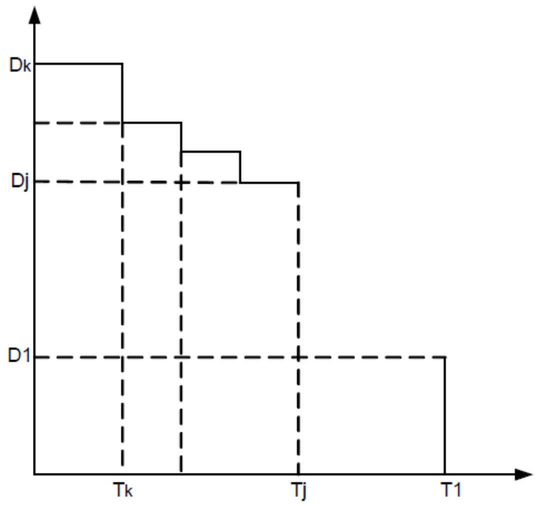

Figure 2.8 Approximated load duration curve [99]

The assessment of DG costs, in particular fuel costs, total demand of a network and generation fluctuated generation of DGs can all be considered as random variables. In such situation, a stochastic generation planning model is needed. In the publication of Mo [85], a stochastic dynamic programming was used to incorporate discrete expansion sizes, correlations and autocorrelations among uncertain variables including fuel prices and demand, and economies of scale in investment costs. Due to the discrepancy in time scales, the overall planning problem was decomposed into investment and operational pieces [83].

2.10 Order of Optimization

Optimal integration of distribution is not only concerning with methods but also with how the optimisation technique is used in order to address the problem comprising challenge of optimal capacity evaluation [87], DG optimal location [88], and optimal sizing [89], [90], [91]. In the literate the approaches could be divided into three classes: Approaches concerning with finding optimal locations for defined DG capacities, finding optimal DG capacities at defined locations, and the combined approach.

2.10.1 Pre-Specified Capacity

In this approach optimisation engine attempts to find the best sites for DGs of specified, discrete, capacities .This approach has been taken in the works of Nara *et al.* [88], Kim *et al.* [92] and Kuri *et al.* [93]. In some literature the assumption is that optimal DG site and size is a multiple of a given capacity [94]. The downfall of pre specifying capacity is that some solutions that are not the equivalent to the standard will not be selected. It will undermine the optimality of the system. To avoid the problem, a large range of capacities should be examined to increase the search space exploration capability [51], [86].

2.10.2 Pre-Specified Location

In the second approach optimisation engine attempts to find DG capacities at each location specified before running it [51]. The methods tend to use continuous functions of capacity solved using method discussed in Section 2.5. The disadvantage of this approach appears where the optimal locations found by the optimisation engine may already contain small DGs suggesting that very small plant would not be economic. Pre-specifying a minimum capacity at each bus would disable the optimisation to find a feasible solution. Choosing a number of best locations out of number of buses is the combinations of *r* locations in a network of *n* buses represented by $\binom{n}{r}$ thus even in a small distribution network, it adds significant burden [95].

2.10.3 Combined Approach

By using search based methods in the optimisation, combined size and location optimisation approach became an option so the complex power system problem was no longer restricted to calculus based methods which treat the DG capacities as continuous variables while their locations remain fixed [15]. The combined approached has widely been taken in the literature

[11], [53], [88], [92], [93] usually running the same method on a particular instance of a problem for several times to obtain the optimised solution. This approach allows exploration of a range of interesting problems but mostly at the expense of predefinition of the number of DG units [51].

2.11 Summary

In this chapter a review of literatures about planning distribution generations in power system network was presented. In Section 2.2 a short history of incorporating DGs into electricity network and their effect on network policies was presented. The literature planning perspective is with respect to finding the optimum capacity and location of candidates DGs. Therefore in Section 2.3 and 2.4 the significance of optimisation was justified in terms of technical and mathematical issues. The issues in optimum placement and location are defined with respect to various objectives which were presented in Section 2.5 as multi-objectiveness. To solve either multi-objectives or single-objective optimisation problem, various numerical and heuristic optimisation techniques have been published. Section 2.6 discussions elaborate on the techniques and their application in solving the optimisation in a power system network. Each technique was discussed in terms of their advantages and disadvantage or their history of development in power system. Following Section 2.6, the properties of the presented techniques were also enumerated. Distribution generations in the calculations are perceived differently in publications hence Section 2.7 presented a review on their size, power injection model and their energy types. Section 2.8 presented main analysis tools and how they are utilised in the optimisation. Section 2.9 is about the view that network operator takes in terms of short or long-term planning or the approximation of load. The last Section 2.10 presents an overview of the way the design variables are programmed in terms of their priorities in optimisation.

Chapter 3

Optimisation Theory and Algorithms

3.1 Introduction

In Chapter 2 an up to date literature review was presented. In this Chapter the attempt is made to represent a background of literature which includes mathematical formulas of applied theories based on Chapter 2 literature. As the optimisation is main goal of the thesis, the first Section of this Chapter addresses this area. The elements of optimisation such as variables and objectives are presented to illustrate how existing approaches could be taken advantages of in DG planning. Heuristic and non-heuristic methods are elaborated in terms of their implementation aspects. For this reason Pseudo codes of heuristics are presented. Distribution generation planning is very dependent on load and generation modelling so the next Section focuses on load and generation studies particularly load flow. As optimisation implies, it is restricted to technical elements. Therefore constraints come next in the Section to provide an insight to those elements. One of the biggest constraints is cost of planning which is the topic of last Section. The value of investment over the horizon years should be considered as well as capital and running cost of added DGs to gives the planner an economic perspective in planning.

3.2 Optimisation Techniques

The need for higher efficiency and effectiveness optimisation tools is increasing to ensure that electrical energy of the standard quality can be provided at the lowest cost / higher reliability. In Chapter 2 applications of various optimisation techniques in power system were presented.

Optimisation is such a broad realm that takes books to articulate; however there are basic elements in all optimisation which are necessary to be discussed here. Due to high non-linearity nature of power system problems, optimisation techniques have been a popular subject in power system. For instance network loss which was discussed in Chapter 2 under technical issues Section 2.2.1 is highly non-linear. The non-linearity of the network real power loss could be understood from equation (3-1a).

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} [\alpha_{ij} \left(P_i P_j + Q_i Q_j\right) + \beta_{ij} \left(Q_i P_j + P_i Q_j\right)] \tag{3-1a}$$

where

$$\alpha_{ij} = \frac{r_{ij}}{V_i V_j} \cos(\delta_i - \delta_j) , \beta_{ij} = \frac{r_{ij}}{V_i V_j} \sin(\delta_i - \delta_j) \tag{3-1b}$$

The elements of every optimisation are its variables, objectives and constraints. There are different type of variables, objectives and constraint in power system optimisation problem as of any their optimisation.

3.2.1 Variables

In any optimisation there are three types of variables: control variables state variables and constraint variables. Control or independent variables such as generator outputs or transformer tap changing, corresponds to those that can be arbitrarily manipulated, within their limits, in order to minimize or maximise the objective function. States or dependant variables such as load bus voltage magnitudes and angles correspond to variables that are set as a result of the controls, but must be monitored. Constraint variables are variables associated with the constraints .In conventional optimisation techniques Lagrangian multipliers is a type of constraint variable [180].

3.2.2 Single-Objective Based and Multi-Objective Approaches

Over the past decades, power system problems utilised single-objective optimisation methods with simplified assumptions to reduce the complexity of the problem [181]. A variety of optimisation techniques have been proposed to solve the problems of optimal integration of DGs in terms of operations and planning for decades [96]. In a broader perspective, literature shows that these techniques could be brought under single objective or multi-objective category applied in reactive power planning or VAR planning, economic/environment dispatch, transmission/distribution network expansion planning, etc. Single-objective optimisations include techniques such as the weighted sum method, the ε-constraint method and the goal programming method, etc. [181]. In weighted sum, the method is to transform all objectives into an aggregated scalar objective function problem by using weighted criteria. One specifies scalar weights for each objective to be optimized, and then combines them into a single function that can be solved by any single-objective optimization method. Determining how to weight different objectives could become problematic in some optimisation techniques particularly in conventional methods, as they require good knowledge of the systems. The ε-constraint method suggests optimizing a single-objective function while dealing with all other objectives as constraints. The goal programming method is based on minimizing a sum of deviation of objectives from user-specified targets. In following these approaches are presented in details.

3.2.2.1 Weighted Method

This approach is in general known as the weighted-sum or scalarization method. It is the simplest and the most famous single objective approach used for to tackle the multi-objective optimization. This approach is based on achievement of conflicting goals by converting a multi-objective optimization problem into a single-objective one [185]. The weighted-sum method minimizes a positively weighted convex sum of the objectives to produce a unique objective function [182]. It is represented in equation (3-2).

$$min \sum_{i=1}^{N} \gamma_i . f_i(x) \quad (3\text{-}2a)$$

$$\sum_{i=1}^{N} \gamma_i = 1 \quad (3\text{-}2\ b)$$

$$\gamma_i > 0 \,, i = 1, \dots \,, N \quad (3\text{-}2\ c)$$

$$x \in S \quad (3\text{-}2\ d)$$

Weighting coefficients γ_i do not necessarily correspond directly to the relative importance of the objective functions. Nevertheless, weight assignment is the most challenging part of the optimization and solving the optimization problem. In this approach optimal solution is highly sensitive to weight selection. Furthermore, weighted-sum method is reliable only when all the data are expressed in exactly the same unit or numerical weights can be precisely assigned to the achievement of each goal [185].

3.2.2.2 ε- constraint Method

ε-constraint method was proposed in 1983 [183]. One objective out of *n* is minimized and the remaining objectives are constrained to be less than or equal to given target values. The problem is defined as the following

$$\min f_2\ (x) \quad (3\text{-}3a)$$

$$f_i(x) \leq \ \varepsilon_i \,, \forall\ i\ \in \{1, \dots, N\} \quad (3\text{-}3b)$$

$$x \in S \quad (3\text{-}3c)$$

One advantage of the ε -constraints method is that it is able to achieve efficient points in a non-convex Pareto curve [182]. The concept of Pareto curve is presented in Section 3.2.2.4.

3.2.2.3 Pareto Based Multi-objective Method

In power system multi-objective optimisation no unique solution can simultaneously optimise all of the objectives of a multi-objective problem as they are normally conflicting. Methods presented above in Sections 3.2.2.1 and 3.2.2.2 which rely on prior assumptions, have been employed to overcome the issue. As opposed to such approaches, the multi-objective problem could directly generate optimum set of points called as Pareto frontier through the use of separate objectives [178]. In general, multi-objective minimisation problem with n decision variables and m objective functions associated with inequality and equality constraints can be mathematically stated as (3-4).

Minimize $F(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_m(\vec{x})]$ (3-4a)

Subject to $h(\vec{x}) \leq 0$ (3-4b)

$g(\vec{x}) = 0$ (3-4c)

where

$\vec{x} = [x_1, x_2, \dots, x_n]$ (3-4d)

Finding a set of trade-off optimal solutions on which no improvement is possible in any objective function without previously sacrificing at least one objective function is called Pareto-optimal solutions [181]. Mathematically $\vec{x}^*$ are called Pareto optimal if there does not exist another $\vec{x}$ such that $f(\vec{x}) \leq f(\vec{x}^*)$ for all objectives .This notion has been shown in Figure 3.1 for a two objective problem.

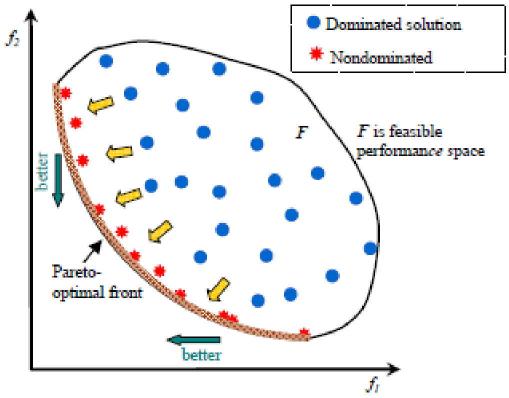

Figure 3.1 f1 and f2 are to be minimised from [181]

3.2.2.4 Goal Programming Method

Goal programming method attempts to find specific goal values of objectives. It is based on minimizing a sum of deviation of objectives from user-specified targets [181]. A set of design goals $t = [t_1, t_2, \dots, t_k]$ are associated with a set of objectives, $f(x) = [f_1(x), f_2(x), \dots, f_m(x)]$. The optimization goal can be formulated as (3-5).

$$f_i(x) = t_i \quad i = 1, \dots, k \tag{3-5}$$

Equation (3-5) can be written using different types. Less than or equal to t as in (3-6)

$$f(x) \leq t \tag{3-6}$$

Greater than or equal to t as in (3-7)

$$f(x) \geq t \tag{3-7}$$

or within a range as in (3-8)

$$f(x) \in [t^{inf}, t^{sup}] \tag{3-8}$$

Two non-negative deviation variables (*n* and *p*) are introduced to satisfy the presented goals from (3-5) to (3-8). In (3-6) the positive deviation *p* is subtracted from the objective function. The deviation *p* quantifies the amount by which the objective function has not satisfied the target *t*. The objective of goal programming is to minimize the deviation *p* as expressed in (3-9)

$$f(x) - p \leq t \, , n = 0 \qquad (3\text{-}9)$$

Similarly for (3-7) the objective is to minimize the deviation *n* so as to find the solution that minimizes the deviation. It is shown in (3-10)

$$f(x) + n \geq t \, , p = 0 \qquad (3\text{-}10)$$

Therefore, to solve a goal programming problem, each goal is converted into at least one equality or inequality restriction, and the objective is to minimize all *p* and *n* deviations. The relative degree of goal achievement is controlled by the vectors of weighting coefficients, w and β, and is expressed as a standard optimization problem expressed in (3-11) [203].

$$Minimize \sum_{j=1}^{k} (w_j p_j + \beta_j n_j) \qquad (3\text{-}10)$$

subject to

$$f(x) - p_j + n_j = t_j \quad j = 1,2, \dots , k \qquad (3\text{-}11)$$

$$x \in \Omega, \quad n_j \, , p_j \geq 0$$

Because of w and β , goal programming depends on the choice of these weighting factors.

3.2.4 Non-Heuristic Optimisation Techniques

Optimisation techniques applied in power system attempt to use models to determine critical operating conditions of a power system to obtain secure power dispatches. The optimal integration DG resources were presented in Chapter 2 from different perspectives but here a more in depth background of the techniques are discussed. The integration techniques are comprised of conventional and heuristic techniques. The first type of methods also known as applied mathematical methods are based on mathematical programming algorithms such as linear and non-linear programming, mixed integer non-linear programming and interior-point methods [96] .The second class of optimisation was introduced as many power system formulations might not be satisfied by strict mathematical assumption particularly if the global optimisation is of interest [184].

3.2.3.1 Linear and Nonlinear Programming

An example of a linear problem is written:

$$\min f\ (x) = ax + b \tag{3-12a}$$

$$g_j(x) = cx + d = 0\ j = 1,2..p \tag{3-12b}$$

$$h_k(x) = rx + s \leq 0\ k = 1,2..q \tag{3-12c}$$

$$x \in \mathbb{R}$$

$$a, b, c, d, r, s \in \mathbb{R}$$

where x is the vector of decision variables. $f\ (x)$ is the objective or goal function. For example objective could be investment, fuel, operation and maintenance and unavailability costs of the system as in [101]. The objective is always to the restrictions given by $g(x)$ the equality and $h(x)$ inequality constraints. a, b, c, d, r and s are the vectors of real numbers that define the linear relationships of the problem. The sum of the powers generated by each group of generation units must be equal to the power that flows from the correspondent fictitious node to the load node or zero node so equality constraints $g(x)$ in that sense would be

$$\sum_{j=1}^{Nu} P_{ij} = P_{i0} \tag{3-13}$$

ij corresponds to the any two branch in the power system network.

Other inequality constraint could vary but most of optimisation techniques applied in DG planning have the following constraints in common:

- maximum power for each group of generators[101]
- minimum capacity of the generator array
- limits on power generated by each generator
- limits on the number of DGs
- possible limits on the location of DGs
- limits on line currents (thermal limit)

The above constraints are discussed in Section 3.4. Any optimisation results should be within these constraints known as feasible region. In nonlinear problems feasible region is bounded by constraints, as illustrated in as Figure 3.2 illustrates an initial solution is estimated, and then the algorithm iteratively approximates to the (local) optima solution.

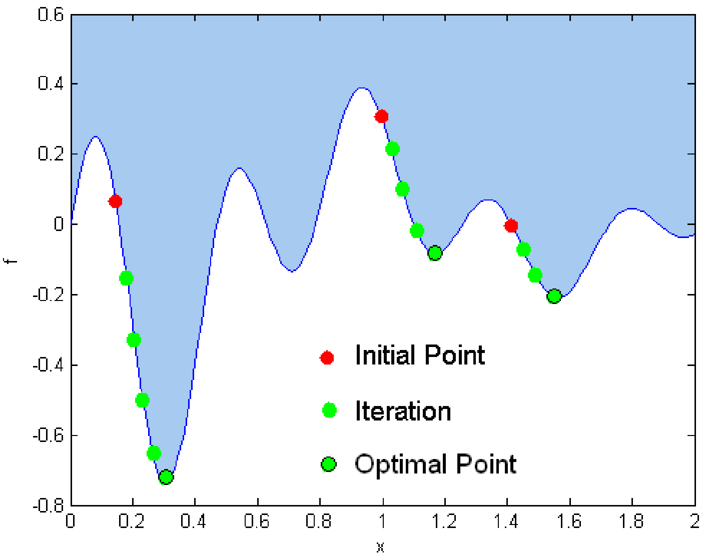

Figure 3.2 Nonlinear optimisation problem (min f(x)=cos (10x).sin (5x).e^{-x}) [98]

The feasible set of the nonlinear programming problem can always be represented as (3-14).

$$C = \{x \in \mathbb{R}^{\mathrm{n}} | \mathrm{h}(x) = 0, \quad \mathrm{l} \le x \le u\} \tag{3-14}$$

where $h: \mathbb{R}^{\mathrm{n}} \to \mathbb{R}^{\mathrm{m}}$ (When an inequality constraint $g(x) \le 0$ appearsin the original formulation it can be replaced by $g(x) + z = 0, z \ge 0$). Feasible methods for solving NLP generate a sequence of approximations $x^k \in \mathrm{C}$ such that $f(x^{k+1})$ is sufficiently smaller than $f(x^k)$ for all k. Reduced gradient belongs to this class of methods. Usually, each iteration of feasible method consists of two phases. In the "predictor phase", given a feasible $y \in \mathrm{C}$ a better approximation z is computed in the tangent set to C that passes through y. In the "corrector phase", feasibility is restored. Starting with (the generally infeasible) z one tries to find a new feasible point x such that $f(x)$ is sufficiently smaller than $f(y)$. In reduced gradient (GRG) methods the restored point is obtained (if possible) by modifying only the value of m basic variables [19].

3.2.3.2 Mixed-Integer Nonlinear Programming

The most basic form of a mixed-integer nonlinear programming (MINLP) problem when represented in algebraic form is depicted in equation (3-15).

$$\min Z = f(x, y) \tag{3-15a}$$

$$s.t.\, g_j(x, y) \le 0 \; j \in J \tag{3-15b}$$

$$x \in X, y \in Y$$

where *f, g* are convex, differentiable functions, *J* is the index set of inequalities, and x and y are the continuous and discrete variables, respectively. The set X is commonly assumed to be a convex compact set, e.g. $X = \{x | x \in \mathbb{R}^{\mathrm{n}}, D_x \le d, x^L \le x \le x^U\}$ the discrete set *Y* corresponds to a polyhedral set of integer points, $Y = \{y | y \in \mathrm{Z}^{\mathrm{m}}, A_y \le a\}$, and in most applications is restricted to 0-1 values, $y \in \{0,1\}^m$. In most applications of interest the objective and constraint functions *f g are* linear in *(*e.g. fixed cost charges and logic constraints). Mixed integer non-linear programming could get different forms such as branch and bound method [18] and generalized bender decomposition method. Branch and bound methods start with a relaxed version of the integer problem. Relations are defined as in equation (3-16).

$$\min Z_{LB}^{k} = f(x,y) \tag{3-16a}$$

$$s.t.\, g_j(x,y) \leq 0 \; j \in J \tag{3-16b}$$

$$x \in X, y \in Y$$

$$y_i \leq \alpha_i^k \;\; i \in \; I_{FL}^k \tag{3-16c}$$

$$y_i \geq \beta_i^k \; i \in \; I_{FU}^k \tag{3-16d}$$

where Y_R is the continuous relaxation of the set Y, and I_{FL}^k, I_{FU}^k are index subsets of the integer variables y_i $i \in I$, which are restricted to lower and upper bounds, α_i^k, β_i^k at the k^{th} step of a branch and bound enumeration procedure [20]. The BB method starts by solving first the continuous NLP relaxation. If all discrete variables take integer values the search is stopped. Otherwise, a tree search is performed in the space of the integer variables y_i, $i \in I$. These are successively fixed at the corresponding nodes of the tree, giving rise to relaxed NLP of the form (3-9) which yield lower bounds in the descendant nodes.

3.2.3.3 Interior Point Method

The first step in every interior point method (IP) is transforming an inequality constrained optimization problem to equality constrained. The next steps are formulating Lagrange function by a logarithmic barrier functions, setting the first order optimality conditions, and applying Newton’s method to the set of equations coming from the first-order optimality conditions [186]. An equality constrained nonlinear optimization problem has the form (3-5a) and (3-5b). The optimality conditions can be formulated using Lagrange function.

$$L(x, y) = f(x) - y^T g(x) \tag{3-17}$$

y is called Lagrange multiplier. The first order optimality conditions are

$$\nabla_x L(x, y) = \nabla f(x) - \nabla g(x)^T y = 0 \tag{3-18}$$

$$\nabla_y L(x, y) = -g(x) = 0 \tag{3-19}$$

An optimal solution to nonlinear (3-10) must satisfy equation (3-12). Newton method is used to solve (3-10). Based on Taylor's theorem in a general smooth nonlinear function $f: \mathbb{R}^{\mathrm{n}} \rightarrow \mathbb{R}^{\mathrm{n}}$

$$f(x) = 0 \tag{3-20}$$

$$f(x^0 + \Delta_x) \cong f(x^0) + \nabla f(x^0)\Delta_x \tag{3-21}$$

x^0 is an initial guess to equation (3-13). Assuming that $\nabla f(x^0)$ is not singular Δ_x defines search direction as equation (3-15).

$$\Delta_x = -\nabla f(x^0) \tag{3-22}$$

New point is calculated from equation (3-16)

$$x^1 = x^0 + \alpha. \Delta_x \tag{3-23}$$

α is called step size scalar and is chosen in the interval (0,1]. Iteratively the solutions are generated until the objective $f(x)$ close enough to zero.

3.2.4 Heuristic Optimisation Techniques

In conventional techniques derivates of functions may not be very useful when the objective is highly variable. The example is shown in Figure 3.3 .

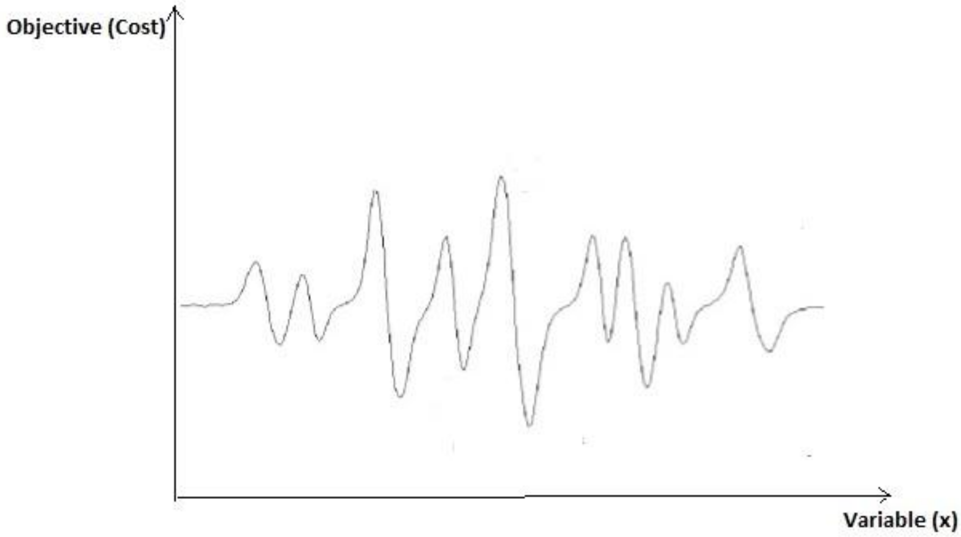

Figure 3.3 A highly variable objective (cost)

In Figure 3.3 cost function is highly variable and methods such as gradient would not yield promising results. Heuristic techniques which are based on population are able to break the space into variety of sub spaces in order to find the optimum (near optimum) point.

3.2.3.4 Simulated Annealing

Simulated annealing (SA) is a refinement of the local search which is illustrated in the following pseudo code.

Pseudo-code for the classical local search procedure

1: Generate initial solution x^c

2: **while** stopping criteria not met **do**

3: Select $x^n \in N(x^c)$ (neighbour to current solution)

4: **if** $f(x^n) < f(x^c)$ **then** $x^c = x^n$

5: **end while**

The stopping criterion is defined by a given number of iterations or a number of consecutive iterations without change/improvement for the current solution [25]. Pseudo code for simulated annealing from the publication of Gilli and Winker [24] is represented as follows:

Pseudo code for simulated annealing

1: Generate initial solution x^c, initialize R_{max} and T

2: **for** $r = 1$ to R_{max} **do**

3: **while** stopping criteria not met **do**

4: Compute $x^n \in N(x^c)$ (neighbour to current solution)

5: Compute $\Delta = f(x^n) - f(x^c)$ and generate u (uniform random variable)

6: **if** $(\Delta < 0)$ or $e^{-\Delta/T} > u$ **then** $x^c = x^n$

7: **end while**

8: Reduce T

9: **end for**

T is the temperature gradually reduced in the process.

3.2.3.5 Tabu Search

Pseudo code from the work of Gilli and Winker [24] is as follows:

Pseudo code for Tabu search

1: Generate current solution x^c and initialize tabu list $T = \emptyset$

2: **while** stopping criteria not met **do**

3: Compute $V = \{x |\ x \in N(x^c)\} \backslash T$

4: Select $x^n = \min(V)$

5: $x^c = x^n$ and $T = T \cup x^n$

6: Update memory

7: **end while**

3.2.3.6 Ant Colony

The significance of the ant colony (AC) algorithms is that each artificial ant works individually but communicates with other ants through the pheromone trails. The pheromone trail could be altered by other ants. This alteration is based on other ants' experiences for their next move so an optimal solution is achieved [40]. Ant Colony pseudo code from the work of Gilli and Winker [24] is as follows:

Pseudo code for ant colony

1: Initialize pheromone trail

2: **while** stopping criteria not met **do**

3: **for** all ants **do**

4: Deposit ant randomly

5: **while** solution incomplete **do**

6: Select next element in solution randomly according to pheromone trail

7: **end while**

8: Evaluate objective function and update best solution

9: **end for**

10: **for** all ants **do** Update pheromone trail (more for better solutions) **end for**

11: **end while**

3.2.3.7 Particle Swarm Optimization

Particle swarm optimization (PSO) technique provides a population-based search process. Solutions are called particles. In the search procedure their position (state) changes with time. Particles fly around in a search space. During flight, the position of each particle is adjusted according to its own experience (this value is called P_{best}), and according to the experience of a neighbouring particle, PSO updates a population of solution vectors by an increment called velocity [43]. The process is illustrated in Figure 3.4.

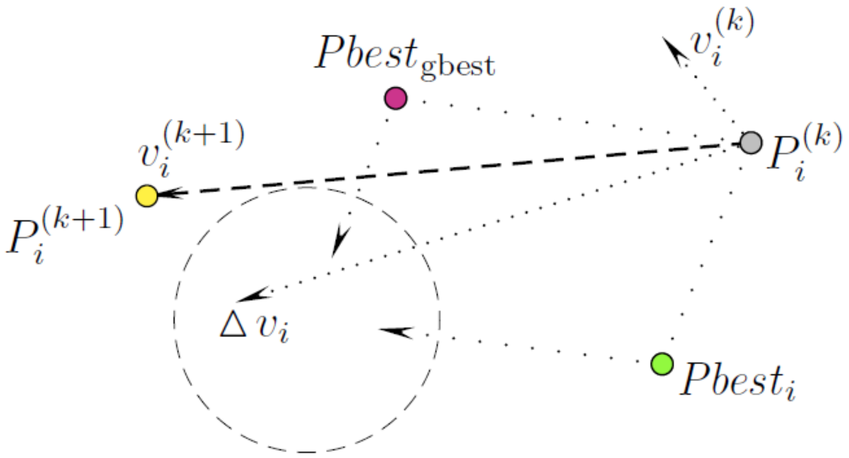

Figure 3.4 Updating the position of a particle P_i^((k)) with velocity [24]

The position of particle in the k^{th} generation $P_i^{(k)}$ gets updated to $k+1^{th}$ generation. There are two directions considered. The direction from the current position of the particle to the best position $(P_i^{(k)} \rightarrow P_{best_i})$ and the direction from the current position to the best position for all particles $(P_i^{(k)} \rightarrow P_{best_{gbest}})$. Both directions are subject to random perturbation by a random number between 0 and 1. The pseudo code for Particle swarm is as follows:

Pseudo code for Particle swarm optimisation

1: Initialize parameters n_p, n_g and c

2: Initialize particles $P_i^{(0)}$ and velocity $v_i^{(0)}$, $i = 1, \dots, n_p$

3: Evaluate objective function $F_i = f(P_i^{(0)})$, $i = 1, \dots, n_p$

4: $P_{best} = P^{(0)}$, $F_{best} = F$, $G_{best} = min_i(F_i)$, $g_{best} = argmin_i(F_i)$

5: **for** k = 1 to n_G **do**

6: **for** i = 1 to n_p **do**

7: $\Delta\, v_i = c\; u\; \left(P_{best_i} - P_i^{(k-1)}\right) + c\; u\; (P_{best_{gbest}} - P_i^{(k-1)})$

8: $v_i^{(k)} = v^{(k-1)} + \Delta\, v_i$

9: $P_i^{(k)} = P_i^{(k+1)} + v_i^{(k)}$

10: **end for**

11: Evaluate objective function $F_i = f\left(P_i^{(k)}\right), i = 1, \dots, n_p$

12: **for** i = 1 to n_p **do**

13: **if** $F_i < F_{best_i}$ **then** $P_{best\ i} = P_i^{(k)}\ and\ F_{best_i} = F_i$

14: **if** $F_i < G_{best}$ **then** $G_{best} = F_i\ and\ g_{best} = i$

15: **end for**

16: **end for**

3.2.3.8 Genetic Algorithm

Crossover creates new candidates for the solution which combines part of the genetic of each previous candidate named as parent. It is then applied a random mutation. Mutation randomly perturbs a candidate solution. In the occurring iterations reproduction keeps the most successful solutions found in a population, discarding the rest from the population pool.
The pseudo code for genetic algorithm from [24] is as follows:

Pseudo code for genetic algorithm

1: Generate initial population *P* of solutions

2: **while** stopping criteria not met **do**

3: Select $P' \subset P$ (mating pool), initialize $P'' = \emptyset$ (set of children)

4: **for** $i = 1$ to *n* **do**

5: Select individuals x^a and x^b at random from P'

6: Apply crossover to x^a and x^b to produce x^{child}

7: Randomly mutate produced child x^{child}

8 : $P'' = P'' \cup x^{child}$

9: **end for**

10: P = survive(P', P'')

11: **end while**

However, combining objectives into one objective in power system problems requires a strong knowledge of exploring space [14] so GA has also been evolved into another form in recent years named as non sorting genetic algorithm (NSGA) introduced by Deb [55].

3.3 Load and Generation Modelling

Electricity load-generation modelling is very importance in the management of power systems. Long-term and short-term load power consumption modelling is required for capacity planning, maintenance scheduling, operation and planning and control of power systems [187], [188]. Loads can be either modelled as constant power or constant impedance. In the publication of Ochoa *et al.* [189] load is modelled as a constant power and represents the maximum and minimum load demand in two different scenarios. However the load modelling is devoid of time variation of load levels. In time variations load modelling approaches, the analysis of load (and also generation) hourly intervals for the horizon of a year or more than a year is presented. It consequently leads to 8760 analysis intervals per year [190]. To overcome the uncertainty of load and generation in a yearly horizon analytical and mathematical modelling is adopted. Deterministic load modelling and probability load flow (PLF) are two adopted approach in distribution generation operation and planning.

3.3.1 Deterministic Load Modelling

In some literature static load condition is adopted. Different load scenarios such as peak load [44] could be considered as distribution system load varies in different time of day. In this load pattern, a single load point is considered in each scenario. In the work of Khalesi *et al.* [195] light, average and peak load levels are conditions in which the optimisation is based upon. To address the security of a system a worst case scenario is defined as full capacity generation at the point of minimum load [7].

3.3.2 Probability Load Flow

Probabilistic load flow (PLF) was introduced as opposed to deterministic load flow which uses specific values of power generations and load demands of a selected network configuration to calculate system states and power flows. Firstly introduced in 70s [191] the uncertainties is modelled as input random variables with probabilistic density functions (PDF) or cumulative density functions (CDF). The output states are calculated as random variables with PDFs or CDFs [192]. Analysis of the distribution network operation and planning under uncertainties takes advantages of PLF to evaluate the impact of renewable energy resources. Based on [191] branch flows are assumed to be linearly related and active and reactive power independent from each other. Furthermore normal distribution and discrete distribution are assumed for the load and generation respectively [194]. In other words in conventional generation dispatch and grid configurations are considered as discrete random variables while and variable generation are treated as continuous random variables [193]. The PLF can be solved numerically, i.e. using a MC method, or analytically, e.g. using a convolution method, or a combination of them [194] so PDFs of stochastic variables of system states and line flows can be obtained. Because of linear assumptions made in analytical PLF, it is less accurate than mathematical approach such as MC. The general form of active and reactive power could be presented in equation (3-16).

$$Y = f(X) \qquad (3\text{-}24)$$

The linearized form can be written as

$$X \cong \hat{X} + A(Y - \bar{Y}) \qquad (3\text{-}25)$$

where

$$A = (\frac{\partial f}{\partial X})|_{X=\hat{X}})^{-1} \qquad (3\text{-}26)$$

A is named as sensitivity coefficient matrix. In deterministic Newton Raphson method the Jacobian matrix A is computed in each iteration whereas in PLF it is calculated once. If a convolution technique is used, the derivate would be expressed as in (3-19).

$$f(X_i) = f(Y_1 - \bar{Y}\ 1) * f(Y_2 - \bar{Y}\ 2) * \ldots * f(Y_n - \bar{Y}\ n) \qquad (3\text{-}27)$$

- Monte Carlo Simulation

Monte Carlo simulation (MCS) is a numerical method to solve the probabilistic load flow (PLF) problem. MC method requires large number of simulations, which is very time-consuming. MC is in principle doing deterministic load flow for a large number of times with inputs of different combinations of nodal power values. Therefore, the exact nonlinear form of load flow equations as shown in equations (3-28) and (3-29) can be used in the PLF analysis.

$$P_i = U_i \sum_{k=1}^{n} U_k \left(G_{ik} \cos\theta_{ik} + B_{ik} \sin\theta_{ik}\right) \qquad (3\text{-}28)$$

$$Q_i = U_i \sum_{k=1}^{n} U_k \left(G_{ik} \sin\theta_{ik} - B_{ik} \cos\theta_{ik}\right) \qquad (3\text{-}29)$$

$$P_{ik} = -t_{ik} G_{ik}\ U^2{}_i + U_i U_k (G_{ik} \cos\theta_{ik} + B_{ik} \sin\theta_{ik}) \qquad (3\text{-}30)$$

$$Q_{ik} = t_{ik} B_{ik} U^2{}_i - B_{ik} U_i{}^2 + U_i U_k (G_{ik} \sin\theta_{ik} - B_{ik} \cos\theta_{ik}) \quad (3\text{-}31)$$

$$Q_{i(sh)} = U^2{}_i B_{i(sh)} \quad (3\text{-}32)$$

where P_i and Q_i are the net active and reactive power injection at bus i. P_{ik} and Q_{ik} are the active and reactive power flows in line ik at the bus i side. U_i and U_k are the voltage magnitude at bus i and k. θ_{ik} is the angle difference between the voltages at bus i and k . G_{ik} and B_{ik} are the real and imaginary part of the corresponding admittance matrix [194].

3.4 Constraints

The optimum integration of distribution generation occurs under certain operating constraints. In literature, various constraints have been considered in the distribution generation planning. Constraints are divided into two classes: equality and inequality constraints. The equality constraints are power conservation limit. These are the power flow equations that govern the power flow in a network and must be satisfied throughout the optimization process [196]. Inequality constraints are such as thermal limit of branches or voltage limit of bus bars. In the following, constraints applied in distribution generation proper planning are presented.

3.4.1 Equality Constraints

The total active and reactive power generation of the traditional generation(P_{GT} and Q_{GT}) and DG units (P_{DGT} and Q_{DGT}) must be equal to total load demand (P_{DT} and Q_{DT}) and the total active and reactive power loss (P_{LT} and Q_{LT}).

$$P_{GT} + P_{DGT} - P_{DT} - P_{LT} = 0 \quad (3\text{-}33)$$

$$Q_{GT} + Q_{DGT} - Q_{DT} - Q_{LT} = 0 \tag{3-34}$$

3.4.2 Inequality Constraints

The inequality constraints denote the limits on physical devices in the power system as well as the limits designed to ensure system maintain in the defined security margin.

3.4.2.1 Voltage Profile Limit

Stability criteria require that bus voltage magnitudes be kept at acceptable levels. Mathematically, such restrictions can be expressed as follows:

$$|V_i^{min}| \leq |V_i| \leq |V_i^{max}| \quad \forall\, i \in \{number\ of\ buses\} \tag{3-35}$$

3.4.2.2 Line Thermal Limit

The line thermal rating is the loading that corresponds to maximum allowable conductor temperature under the assumption of thermal equilibrium [198].The power carrying capacity of feeders is represented by MVA limits (S_k) through any branch (k) must be well within the maximum thermal capacity (S_k^{max}) of the lines [197].

$$S_k \leq S_k^{max} \ \forall\, i \in \{number\ of\ branhes\} \tag{3-36}$$

3.4.2.3 Phase Angle Limit

The bus voltage angle δ_i at bus i is restricted by its upper and lower limits for all buses .

$$\delta_i^{min} \leq \delta \leq \delta_i^{max} \ \forall\, i \ \in \{number\ of\ buses\} \tag{3-37}$$

3.4.2.4 Active and Reactive Power Generation Limit

The generated power from both traditional generator and installed DGs represented by P_{gen} and Q_{gen} must be restricted by its lower and upper limits.

$$P_{gen}^{min} \leq P_{gen} \leq P_{gen}^{max} \tag{3-38}$$

$$Q_{gen}^{min} \leq Q_{gen} \leq Q_{gen}^{max} \tag{3-39}$$

3.4.2.5 Substation Transformer Capacity Limit

The total power supplied by the substation transformer S_{load}^{total} should be within the substation's transformer capacity limit (S_{sst}^{max}).Another reason for limiting power in substation is that exporting power beyond the substation (reverse flow of power though distribution substation), will lead to very high losses [6].Hence the substation power transmission should be limited.

$$S_{load}^{total} \leq S_{sst}^{max} \tag{3-40}$$

3.4.2.6 Number of DG Limit

The total number of DGs to be placed in a distribution network has to be bounded by a maximum number of DGs (N_{DG}^{max}).

$$N_{dg} \leq N_{DG}^{max} \tag{3-41}$$

3.4.2.7 Short Circuit Level/Ratio Limit

A short circuit calculation is considered to ensure that fault current with DG (SCL_{rated}) should not increase rated fault current of currently installed protective devices.

$$SCL_{WDG} \leq SCL_{rated} \tag{3-42}$$

In addition, in transient studies short circuit ration limit could be taken into account. Short circuit ratio is the ratio of generator power (P_{DG}) at each bus to short circuit level at each bus (SCL_{BUS}).If the short circuit ratio remain less than 10%, as European standard EN50160, 1994 suggests, the system will remain stable [197].

$$\frac{P_{DGi}}{SCL_i . Cos\ (\emptyset)} \times 100 \leq 10\% \quad \forall\, i \in \mathbb{N} \tag{3-43}$$

3.4.2.8 Power Factor Limit

Distributed generators have been assumed to operate in power factor control mode. This necessitates a constraint on power factor.

$$Cos\ (\emptyset_{DG}) = {}^{\mathrm{P}}\big/_{\sqrt{\mathrm{P}_{\mathrm{DG}}^2 + \mathrm{Q}_{\mathrm{DG}}^2}} = \text{constant} \tag{3-44}$$

where, P_{DG} is real power output of DG, Q_{DG} is reactive power output of DG, and $\emptyset_{DG}$ is constant power factor angle of DG.

3.4.3 Curtailment Limitations

Curtailed energy means energy which could have been generated but was not, due to curtailment forced by use-of-network limitations [199]. In curtailment some of DG power is temporarily reduced or directed to a dump load. The power exported is limited to the maximum power that does not cause the local network voltage to exceed its limit. This varies with the time of day and season.

3.5 Planning Cost

DG reduces the system's capital cost by deferring distribution facilities [202]. However, it incurs costs which should be calculated. Alongside of minimising the environmental impacts and maximisation of the system reliability, minimise costs is one of the major objectives of the distribution generation planning. In planning, total cost is normally defined as the sum of the discounted (present value) of the investment cost for newly added DGs, fixed operational and maintenance (O&M) and variable operational costs for newly added and existing generation units [177]. As the planning occurs in a 5 to 20 year horizon the value of money also changes; hence "present worth value" and "discount rate" are defined to consider this effect. Based on equation (3-45) if the present worth factor P is equal to 0.9 the value of an asset worth £100 (X) after a year would be 90.

$$Value\ today\ of\ X\ pounds\ t\ years\ ahead = X \times \mathrm{P}^{\mathrm{t}} \quad (3\text{-}45)$$

Present worth factor discounts the value of future costs because they lie in the future [201]. The discount rate (d) used in invest cost formula is the year to year reduction in value. If d = 11.11%, £ 111.11 a year from now is worth 100 today. So the present worth is expressed as equation (3-46).

$$P(t) = 1\,/(1+d)^{\mathrm{t}} \quad (3\text{-}46)$$

where t is future year. For a year $t = 1$.

3.5.1 Investment Cost

$$C_1 = \sum_{t\in T}\sum_{n\in N_{new}} d_t(i_{nt} - s_{nt})p_{nt}u_{nt} \quad (3\text{-}47)$$

where T is length of planning horizon, N_{new} is newly installed DGs. d_t is discount rate, i_{nt} and s_{nt} are investment cost and salvage value of added DG in time period (£/MW) respectively. p_{nt} is power capacity of DG_n in time period t (MW). u_{nt} is either 0 or 1 representing the presence of DG_n at time period t.

3.5.2 Fixed Operational and Maintenance Cost

Fixed cost is a one-time cost that is spent during construction and installation and does not depend on loading variation to be served after operation. It consists of construction, installation, equipment, land, permits, site developing and preparation, taxes, insurance, labour, and testing costs [202]. The cost is expressed in equation (3-48).

$$C_2 = \sum_{t\in T} \sum_{n\in N} d_t f_{nt} p_{nt} X_{nt} \tag{3-48}$$

where N is number of generating units, f_{nt} is fixed operational and maintenance cost of DG_n (£/MW) and X_{nt} is cumulative number of nth generating unit up to time period.

3.5.3 Generation (Variable or Running) Cost

A variable (running) cost exists as the system is in service .It depends on the loading required including the cost of fuel, electric system losses, inspection, maintenance, and regular modification like parts replacement, taxes, and insurance [202]. This is expressed in (3-49).

$$C_3 = \sum_{t\in T} \sum_{n\in N} d_t v_{nt}\, g n_{nt} \tag{3-49}$$

v_{nt} is variable operational and maintenance cost of generating unit n in time period t (£/MW).

3.5.4 Annual DG Cost

In some literature cost of DGs is expressed in terms of their levelized value. It involves finding a constant annual cost over a lengthy period of time .In general the present worth Q, levelized over the next n years is expressed as

$$Q_{Levelized} = Q(d \times (1 + \mathrm{d})^{\mathrm{n}})/((1 + d)^n - 1) \tag{3-50}$$

Levelized cost presents the real value of the total cost of building and operating a generating plant over its economic life converted to equal annual payments. Costs are levelized in real currency (here pound sterling) to remove impact of inflation.

3.6 Summary

In this Chapter a theoretical background of DG planning optimisation techniques and methods as well as the element of optimisation such as constraints and cost was presented. The focus of this Chapter was to provide a background on DG planning optimisation and different route taken to achieve this goal. For this reason the mathematical formulas of different related equations were defined in Section 3.2.The correlation of optimisation methods and variables were represented in Figures to demonstrate the objectives and restrictions of equations. As every optimisation techniques, discussed in literature is converted to computer codes for the application in power system, the pseudo codes of most popular techniques in the literature were also presented. Load flow calculation, as the basis of all optimisation in power system, was discussed in Section 3.3 with respect to the theory and different approach for their modelling. Section 3.4 presented the theory on the practical limitations in power system and how and what type of constraints are represented and applied in planning. The last Section presented a theory on economics of DG investments and its representation over a period of time considered for the planning purpose.

Chapter 4

Non-Sorting Genetic Algorithm-II and Implementation for Power System

4.1 Introduction

The attempt in Chapter 3 was to give an insight in theories applied in power system distribution generation planning. The optimisation technique in this thesis is based on multi-objective evolutionary algorithm known as non-dominated sorting genetic algorithm II (NSGA-II). As its name implies, NSGA-II is a developed version of genetic algorithm hence the concept is introduced at the beginning of the Chapter as well as benchmark functions to evaluate the performance of it compared to GA. The Chapter 4 then presents a description on implementation of the theories presented so far for power system design objectives. NSGA-II is coded in MATLAB in order to be utilized in finding optimum size and location in the power system which is the next topic in this Chapter. In this topic the discussion on how MATPOWER is linked to the optimisation engine is discussed. MATPOWER is a package of MATLAB M-files for solving power flow problems [208]. Power system characteristics and constraints are translated to code through objective functions and constraints in the next topic. As the code is MATLAB based, *.m files are tailored for the DG planning. As the core of the NSGA-II is adopted from a work done by Deb [55], variables, functions and constraints have been redefined based on the power flow calculations. The power flow parameters are passed back and forth in a loop in each NSGA generation of solutions until the maximum number of generation is expired. The flowchart of how the programs works is also included to make the coding and programming process more understandable.

4.2 Genetic Algorithm

As discussed in Chapter 3, Genetic algorithm (GA) is a search heuristic that mimics the process of natural selection. By simulating the survival of the fittest among string structures, the optimal string (solution) is searched by randomised information exchange. In every generation, a new set of artificial strings is created using bits and pieces of the fittest of the old ones [204]. GA has been very successful in finding optimum location problem. Also it is simple and easy to implement the code as it can have as many positions as the number of bus candidate to DG connection defined as binary a vector [14]. The GA approach to optimization is typically to encode potential solutions to the problem as fixed length binary strings. A population of these individuals are evaluated by a fitness function. An objective functions measures how well a potential solution will solve the problem. In GA, the complexity (length of the binary strings) must be specified at the start. A genetic algorithm works by building a population of chromosomes which is a set of possible solutions to the optimization problem. Within a generation of a population, the chromosomes are randomly altered in hopes of creating new chromosomes that have better evaluation scores. The next generation population of chromosomes is randomly selected from the current generation with selection probability based on the evaluation score of each chromosome

4.2.1 Initialization

Initialization involves setting the parameters for the algorithm, creating the scores for the simulation, and creating the first generation of chromosomes. In a standard GA seven parameters are set:

- The genes value is the number of variable slots on a chromosome
- The codes value is the number of possible values for each gene
- The population size is the number of chromosomes in each generation
- Crossover probability is the probability that a pair of chromosomes will be crossed

- Mutation probability is the probability that a gene on a chromosome will be mutated randomly
- The maximum number of generations is a termination criterion which sets the maximum number of chromosome populations that will be generated before the top scoring chromosome will be returned as the search answer
- Generations with no change in highest-scoring (elite) chromosome is the second termination criterion which is the number of generations that may pass with no change in the elite chromosome before that elite chromosome will be returned as the search answer

The attempted optimisation is to find the code for each gene in the solution chromosome that maximizes the average score for the chromosome. Finally, the first generation of chromosomes are generated randomly [206].

4.2.1 Evaluation

Each of the chromosomes in a generation must be evaluated for the selection process. This is accomplished by looking up the score of each gene in the chromosome, adding the scores up, and averaging the score for the chromosome. As part of the evaluation process, the elite chromosome of the generation is determined.

4.2.2 Selection and Reproduction

Chromosomes for the next generation are selected using the roulette wheel selection scheme [207] to implement proportionate random selection. Each chromosome has a probability of being chosen equal to its score divided by the sum of the scores of all of the generation's chromosomes. In order to avoid losing ground in finding the highest-scoring chromosome, elitism [207] has been implemented in this benchmark. Elitism reserves two slots in the next generation for the highest scoring chromosome of the current generation, without allowing that chromosome to be crossed over in the next generation. In one of those slots, the elite chromosome will also not be subject to mutation in the next generation.

4.2.3 Crossover

In the crossover phase, all of the chromosomes (except for the elite chromosome) are paired up, and with a probability they are crossed over. The crossover is accomplished by randomly choosing a site along the length of the chromosome, and exchanging the genes of the two chromosomes for each gene past this crossover site [206].

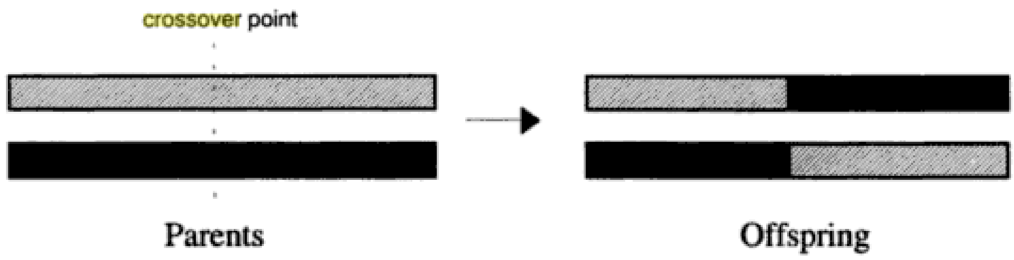

Figure 4.1 Example of one point crossover [206]

4.2.4 Mutation

After the crossover, for each of the genes of the chromosomes (except for the elite chromosome), the gene will be mutated to any one of the codes. With the crossover and mutations completed, the chromosomes are once again evaluated for another round of selection and reproduction.

4.3 Non-dominated Sorting Genetic Algorithm II

Non-dominated sorting genetic algorithm II (NSGA-II) was introduced in 2002 by Deb [55] to tackle the high computational complexity of genetic algorithm and other similar multi-objective evolutionary algorithms.

4.3.1 Improvement in Non-dominated Sorting Genetic Algorithm

NSGA-II is an improved version of NSGA. NSGA algorithm is based on several layers of classifications of the individuals. Before selection is performed, the population is ranked on the basis of non-domination. All non-dominated individuals are classified into one category. The diversity is maintained classified individuals are shared with their dummy fitness values, then this group of classified individuals is ignored and another layer of non-dominated individuals is considered. However as classification of individuals is not very efficient in NSGA, NSGA-II was introduced. As shown in Figure 4.2 builds a population of competing individuals, ranks and sort each individual to create offspring and combines parents and offspring before partitioning the new combined pool into front. A crowding distance is applied to each member which is used in its selection operator to keep a diverse front [205].

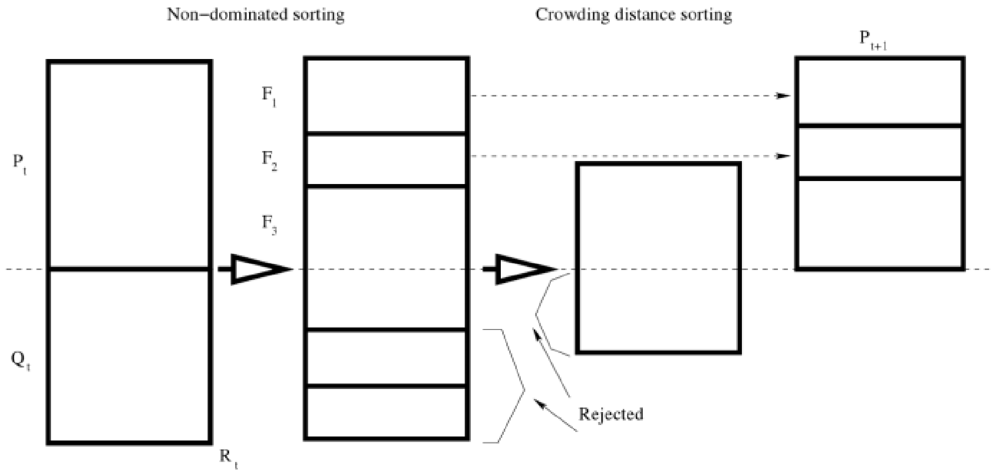

Figure 4.2 Flow diagrams that shows the way NSGA-II works. Pt and Qt are the parents and offspring population at the generation t.F1 are the best solutions from the combined populations.F2 are the second best solutions and so on [205]

A problem with M objectives and N populations in a non-dominated sorting size has a complexity of O (MN^3) in NSGA. By improving the algorithm in NSGA-II the overall complexity is reduced to O (MN^2). Furthermore diversity and speed of NSGA-II is also improved [55]. The flowchart of NSGA-II is depicted in Figure 4.3.

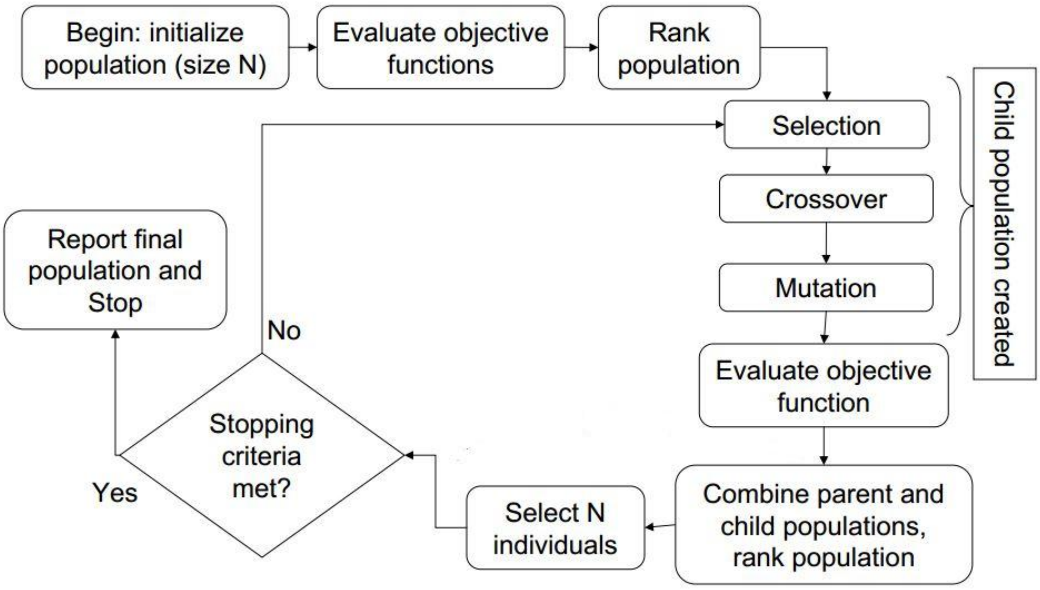

Figure 4.3 Flowchart of NSGA-II [219]

4.3.2 Benchmarking Functions

As NSGA rely heavily on random number generators, benchmarking functions are used in order to evaluate the performance of it in reaching the global solution. Most widely-used benchmark functions are Rastrigin, Griewank, and Sphere which have a value of 0 at the minimum point [zero, zero] in the coordinates.

4.3.2.1 Rastrigin Function

Rastrgin function is defined as equation (4-1).

$$Ras(x) = 20 + x_1^2 + x_2^2 - 10(\cos 2\pi x_1 + \cos 2\pi x_2) \tag{4-1}$$

As demonstrated in Figure 4.4 Rastrigin is a function with many local minima but one global occurring at the point [zero zero] [216].

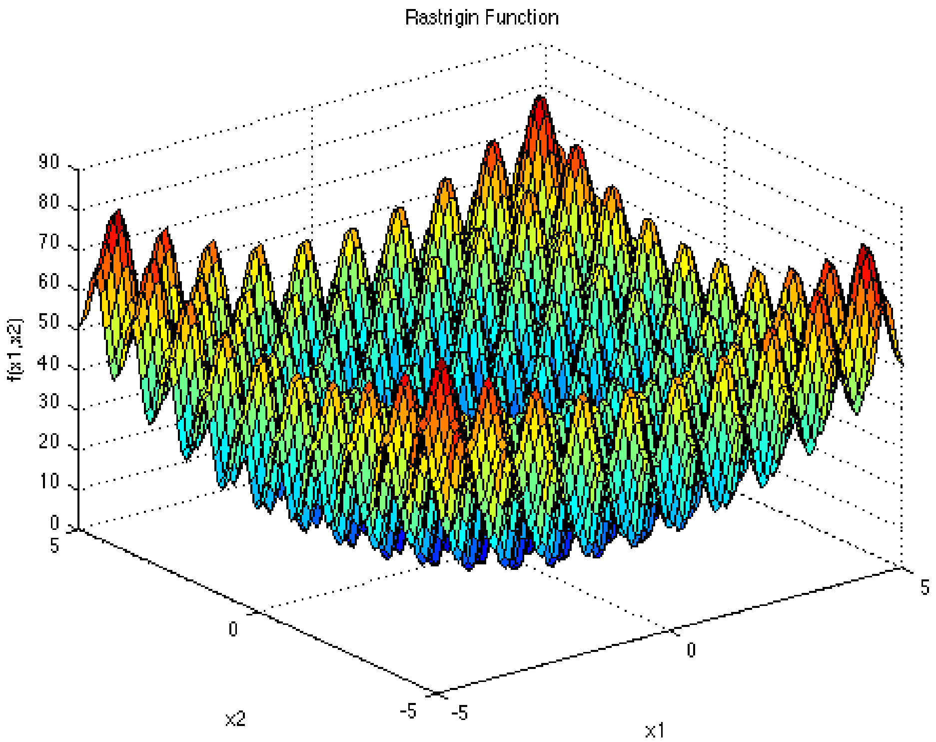

Figure 4.4 Two-dimensional Rastrigin function [216]

Number of design variables are set to 1 (one dimensional) and upper and lower bound are set from -5000 to 5000. As the NSGA-II program is design for more than one objective, two objectives are defined as equal. The lower band and upper band are set the same. Population size and maximum generation are set to 50 and 200 respectively. As one dimensional Rastrigin has one design variable and one objective, the number of design variables are set to 2 as shown in Table 4.1

Table 4.1 Specifying optimisation model in NSGA-II in Matlab

```
options = nsgaopt();                        % create default options
options.popsize = 50;                       % population size
options.maxGen  = 200;                       %max generation
options.numObj = 2;                         % number of objectives
options.numVar = 2;                         % number of design variables
options.numCons = 0;                        % number of constraints
options.lb = [-5000  -5000];                % lower bound of x
options.ub = [5000    5000];                % upper bound of x
options.objfun = @rastrigin_func_obj;       % objective function
options.plotInterval = 5;                   % interval between two calls
result = nsga2(options);                    % begin the optimization
```

The second step in defining the problem in NSGA-II is to create Rastrigin objective function. The objective function is specified by options.objfun parameter created by the function nsgaopt().x illustrated in Table 4.2

Table 4.2 Creating Rastrigin objective function in NSGA-II

```
y = [0,0];
cons = [];
% Objective function : Test problem 'rastrigin'
d = 1;
sum = 0;
for ii = 1:d

    sum = sum + (x(1)^2 - 10*cos(2*pi*x(1)));
end

y(1)  = 10*d + sum;
y(2)  = 10*d + sum;
```

x is the design variables vector which its length must be equal to length of options.numVar. y is the objective values vector which its length must be equal length of options.numObj. After running the NSGA-II the solutions are illustrated in a 2-D space as Figure 4.5

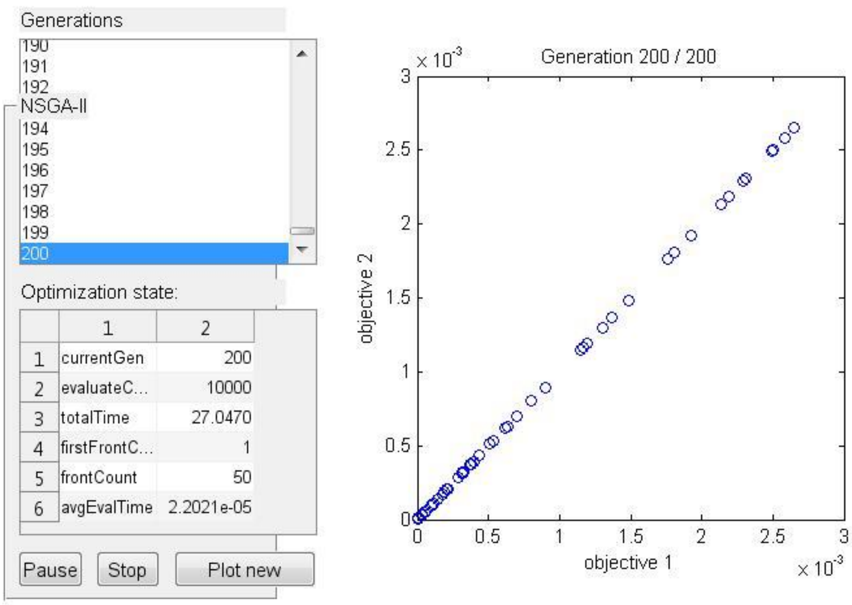

Figure 4.5 Depiction of two Rastrigin function in NSGA-II optimisation

Any of objective 1 or objective 2 in the optimisation should ideally be 0. Figure 4.5 shows the results have converged toward 0. However in order to get numerical values for the design variable and objective function, the last generation of population in NSGA-II is brought in Table 4.3.

Table 4.3 Numerical results obtained from figure 4.5 for Rastrigin function

x1	x2	Objective function (y1)	Objective function (y2)
1.13E-05	1.05359	2.55E-08	2.55E-08
-0.00014	-0.18874	3.72E-06	3.72E-06
-0.00019	-0.28141	7.11E-06	7.11E-06
-0.00021	-1.54046	9.12E-06	9.12E-06
0.000382	1.89638	2.90E-05	2.90E-05
0.000403	1.52715	3.22E-05	3.22E-05
0.000427	0.287396	3.61E-05	3.61E-05
0.0005	-0.07304	4.97E-05	4.97E-05
-0.00053	-0.19094	5.49E-05	5.49E-05
-0.00069	-2.36221	9.38E-05	9.38E-05
0.000725	0.570738	0.000104	0.000104
-0.00076	-0.17046	0.000114	0.000114
-0.00084	0.911065	0.00014	0.00014
-0.00094	0.672011	0.000175	0.000175
0.000975	-1.62829	0.000189	0.000189
-0.00102	-1.42237	0.000207	0.000207
0.001031	-0.64148	0.000211	0.000211
0.0012	-0.11216	0.000286	0.000286
0.001259	-1.42544	0.000314	0.000314
0.001261	-1.59871	0.000316	0.000316
-0.00127	-0.70056	0.00032	0.00032
0.001281	-1.34025	0.000325	0.000325
-0.00137	-0.6321	0.000372	0.000372
0.001376	-0.65282	0.000375	0.000375
-0.00141	-0.04805	0.000394	0.000394
-0.00149	1.6961	0.000438	0.000438
-0.00161	0.912579	0.000512	0.000512
-0.00164	-0.66005	0.000535	0.000535
-0.00176	0.137743	0.000617	0.000617
-0.00178	-2.60601	0.000632	0.000632
0.001876	0.66181	0.000698	0.000698
0.002013	1.05228	0.000804	0.000804
-0.00213	0.418779	0.000896	0.000896
-0.00241	-0.81313	0.001149	0.001149
-0.00242	1.95225	0.001165	0.001165
0.00245	-2.01123	0.001191	0.001191
0.002561	-0.67277	0.001301	0.001301

0.002625	1.31758	0.001367	0.001367
0.002733	-0.8192	0.001482	0.001482
0.00298	0.036302	0.001761	0.001761
-0.00302	-1.46323	0.001808	0.001808
0.003112	-1.27657	0.001921	0.001921
0.003279	-1.0339	0.002133	0.002133
0.003321	-0.8797	0.002188	0.002188
-0.0034	-1.22207	0.002295	0.002295
0.003414	0.289927	0.002312	0.002312
0.003546	2.22896	0.002494	0.002494
-0.00355	-0.15683	0.002503	0.002503
0.003607	0.249731	0.002582	0.002582
-0.00365	2.15033	0.002649	0.002649

The average result from Rastrigin objective function is $8.32 * 10^{-4}$ which is close to zero.

Rastrigin function is also applied in GA in Matlab optimisation toolbox. Fitness function for GA solver is with one variable result is $70 * 10^{-4}$ which is further than point zero compared to NSGA-II. The GA result snapshot is illustrated in Figure 4.6.

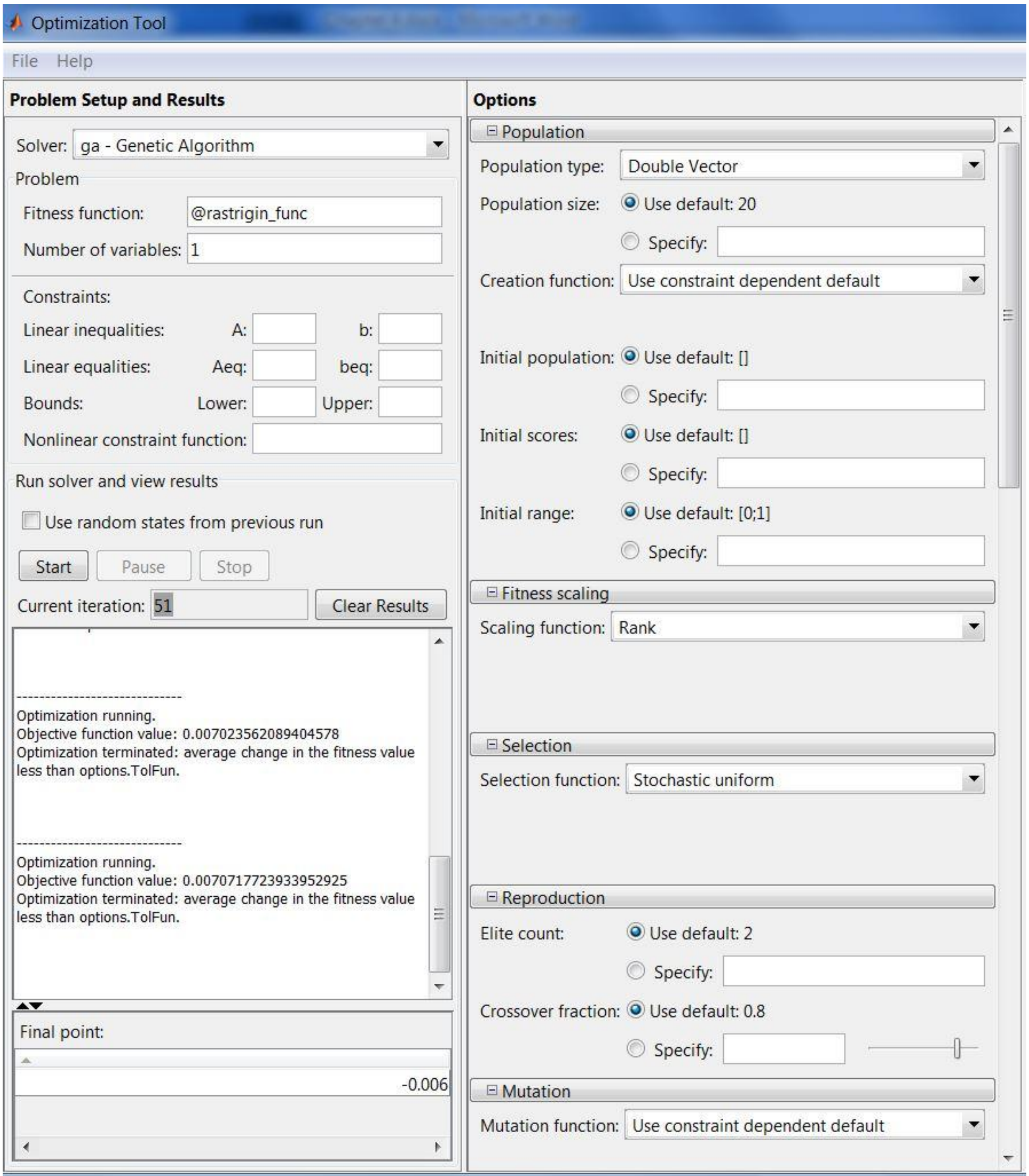

Figure 4.6 GA optimisation result for Rastrigin in Matlab optimisation toolbox

4.3.2.2 Griewank Function

Griewank function is defined as equation (4-2).

$$f(x) = \sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod\nolimits_{i=1}^{d} (\cos \frac{x_i}{\sqrt{i}}) + 1 \qquad (4\text{-}2)$$

The Griewank function has many local minima which are regularly distributed. The complexity is shown in Figure 4.7 for a d=2 dimensional space.

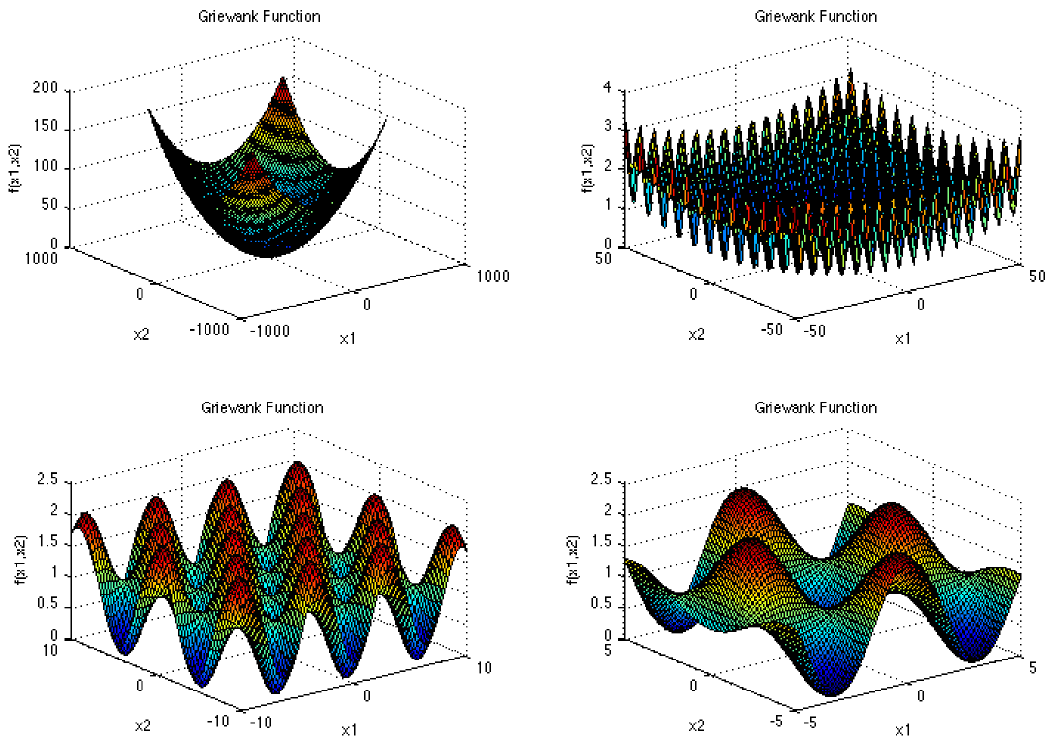

Figure 4.7 Two-dimensional Griewank function shown in different range [217]

The global minimum occurs as zero. Griewank objective function is defined in NSGA-II as Table 4.4.

Table 4.4 Creating Griewank objective function in NSGA-II

```
function [y, cons] = griewank_func_obj(x)
% Objective function : Test problem 'griewank'.
y = [0,0];
cons = [];
d = 1;
sum = 0;
prod = 1;
for ii = 1:d
sum = sum + x(1)^2/4000;
    prod = prod * cos(x(1)/sqrt(ii));
    sum = sum + x(2)^2/4000;
    prod = prod * cos(x(2)/sqrt(ii));

y(1)=sum-prod+1;
y(2)=sum-prod+1;

end
```

After running the NSGA-II the solutions are illustrated in a 2-D space as Figure 4.8.

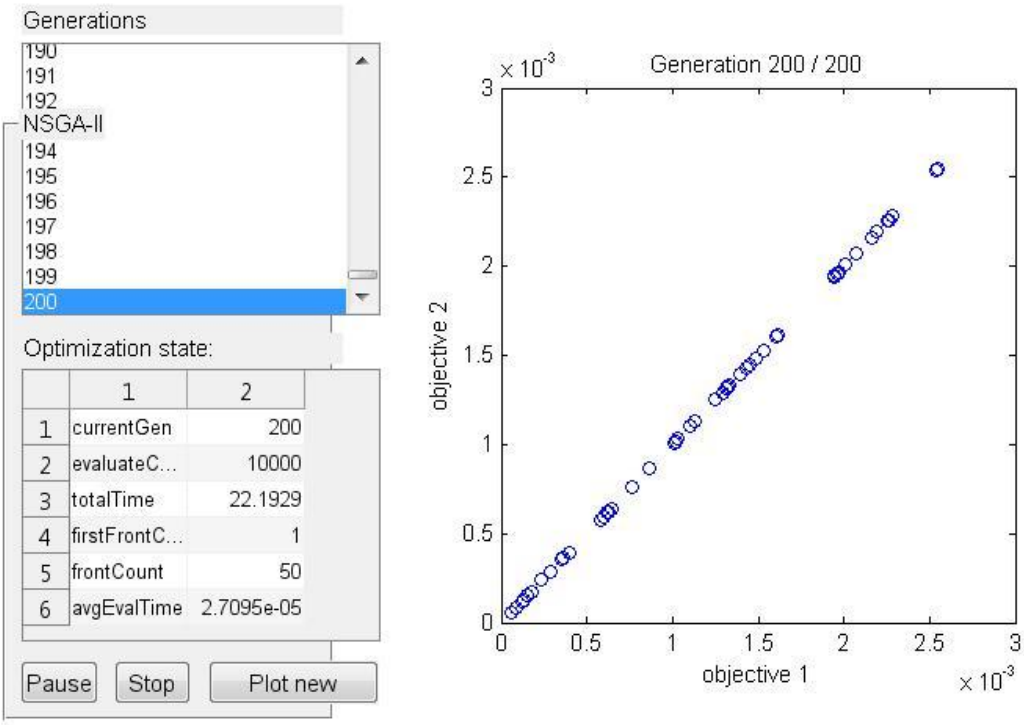

Figure 4.8 Depiction of two Griewank function in NSGA-II optimisation

The design variables and Griewank values are shown in Table 4.5.

Table 4.5 Numerical results obtained from figure 4.8 for Griewank function

x1	x2	Objective function (y1)	Objective function (y2)
-0.00665	-0.00845	5.78E-05	5.78E-05
0.012725	-0.00246	8.40E-05	8.40E-05
0.003999	0.014973	0.00012	0.00012
-0.01568	0.003963	0.000131	0.000131
0.00232	0.017158	0.00015	0.00015
0.018473	-0.00307	0.000175	0.000175
-0.00379	0.021459	0.000238	0.000238
-0.00054	0.02399	0.000288	0.000288
0.018594	0.019096	0.000355	0.000355
0.018331	0.019715	0.000362	0.000362
-0.00928	0.026482	0.000394	0.000394
-0.02499	-0.02305	0.000578	0.000578
0.018952	0.028907	0.000598	0.000598

-0.02891	0.020135	0.000621	0.000621
-0.00377	0.035092	0.000623	0.000623
-0.00724	0.035071	0.000641	0.000641
-0.02865	-0.02641	0.000759	0.000759
0.038997	0.014304	0.000863	0.000863
-0.03351	-0.02991	0.001009	0.001009
-0.03658	0.026498	0.00102	0.00102
0.045054	-0.00596	0.001033	0.001033
0.045926	0.009824	0.001103	0.001103
0.04514	0.01514	0.001134	0.001134
-0.0059	-0.04966	0.001251	0.001251
0.042742	-0.02752	0.001292	0.001292
0.047744	-0.01874	0.001316	0.001316
0.047473	0.019633	0.00132	0.00132
-0.01405	0.049637	0.001331	0.001331
-0.0433	-0.03036	0.001399	0.001399
-0.04177	-0.03351	0.001434	0.001434
-0.05383	0.001597	0.00145	0.00145
0.046646	-0.02819	0.001485	0.001485
-0.04755	0.028237	0.001529	0.001529
-0.0272	0.049748	0.001607	0.001607
-0.01091	0.055725	0.001612	0.001612
0.013286	-0.0609	0.001943	0.001943
-0.05916	0.019785	0.001946	0.001946
-0.05114	-0.03612	0.00196	0.00196
0.027406	-0.05648	0.00197	0.00197
0.019242	-0.06044	0.002012	0.002012
0.026658	0.058549	0.002069	0.002069
0.002305	0.06572	0.002163	0.002163
-0.04006	0.052743	0.002193	0.002193
-0.05357	-0.0406	0.002259	0.002259
-0.00756	-0.06678	0.002259	0.002259
-0.06683	-0.00724	0.00226	0.00226
-0.05605	0.03764	0.002279	0.002279
0.061696	-0.02759	0.002284	0.002284
0.067396	-0.02317	0.002539	0.002539
0.004634	-0.07121	0.002547	0.002547

The average value of Griewank function extracted from Table 4.5 is $1.24 * 10^{-3}$ which is very close to the local minima zero. The objective value in GA is $1.75 * 10^{-4}$.

4.3.2.3 Sphere Function

Sphere function is defined as equation (4-3).

$$f(x) = \sum_{i=1}^{d} x_i^2 \tag{4-3}$$

As demonstrated in Figure 4.9 Sphere is a function with one global minimum occurring at the point [zero zero] in a 2D space [218].

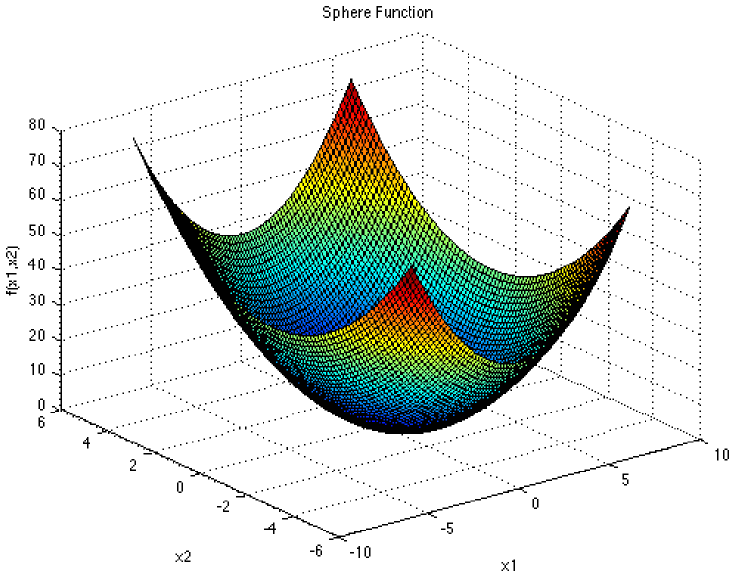

Figure 4.9 Two-dimensional Sphere function [218]

Sphere objective function is defined in NSGA-II as Table 4.6.

Table 4.6 Creating Sphere objective function in NSGA-II

```
function [y, cons] = sphere_func(x)

y = [0,0];
cons = [];


y(1) = sum(x(1).*x(1), 2);
y(2)=sum(x(1).*x(1), 2);
```

Running NSGA-II for Sphere function the Figure 4.10 is obtained.

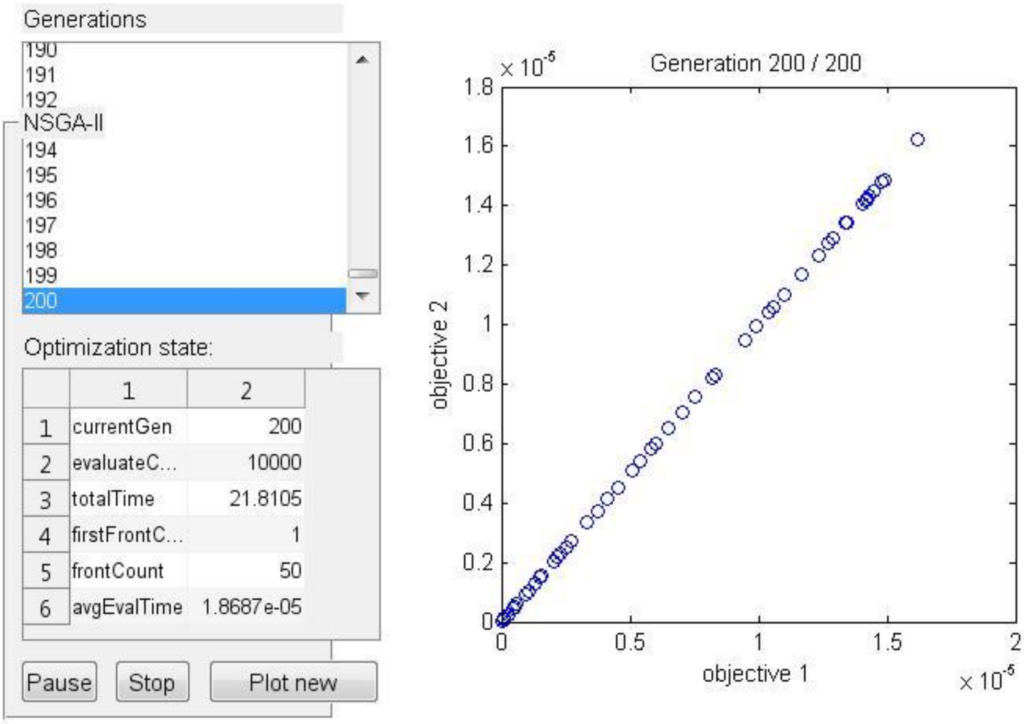

Figure 4.10 Representation of Sphere function in NSGA-II

The population data extracted from 4.10 is represented in Table 4.7.

Table 4.7 Numerical results obtained from figure 4.10 for Sphere function

x1	x2	objective function (y1)	objective function (y2)
-2.84E-06	2.05643	8.05E-12	8.05E-12
0.000318	1.22841	1.01E-07	1.01E-07
-0.00033	0.677294	1.09E-07	1.09E-07
0.000344	3.00756	1.18E-07	1.18E-07
0.0005	-0.38494	2.50E-07	2.50E-07
0.00066	1.76799	4.35E-07	4.35E-07
-0.00071	2.46865	5.04E-07	5.04E-07
-0.00077	0.253847	5.88E-07	5.88E-07
-0.00096	0.245169	9.25E-07	9.25E-07
-0.00102	-0.22657	1.04E-06	1.04E-06
0.001139	2.50175	1.30E-06	1.30E-06
0.001234	0.518075	1.52E-06	1.52E-06
0.001252	1.76465	1.57E-06	1.57E-06
0.001429	2.05266	2.04E-06	2.04E-06

0.001471	-0.20379	2.17E-06	2.17E-06
-0.00151	4.83346	2.28E-06	2.28E-06
-0.00159	0.36375	2.53E-06	2.53E-06
-0.00165	0.301775	2.73E-06	2.73E-06
-0.00183	2.48137	3.34E-06	3.34E-06
0.00193	3.02346	3.73E-06	3.73E-06
0.002035	2.6622	4.14E-06	4.14E-06
-0.00213	0.52973	4.52E-06	4.52E-06
0.002254	2.41821	5.08E-06	5.08E-06
0.002327	2.69397	5.41E-06	5.41E-06
-0.00242	-1.03824	5.84E-06	5.84E-06
0.002452	3.72479	6.01E-06	6.01E-06
-0.00255	0.715182	6.51E-06	6.51E-06
0.002659	1.27894	7.07E-06	7.07E-06
-0.00275	2.85821	7.56E-06	7.56E-06
-0.00287	-0.14653	8.22E-06	8.22E-06
-0.00289	0.984226	8.33E-06	8.33E-06
-0.00308	1.04962	9.49E-06	9.49E-06
-0.00315	1.55341	9.93E-06	9.93E-06
0.003228	3.28419	1.04E-05	1.04E-05
-0.00325	2.40346	1.06E-05	1.06E-05
-0.00332	3.03454	1.10E-05	1.10E-05
-0.00342	1.77666	1.17E-05	1.17E-05
0.003514	2.36098	1.23E-05	1.23E-05
0.003569	3.50778	1.27E-05	1.27E-05
0.003593	2.2046	1.29E-05	1.29E-05
0.003662	0.606202	1.34E-05	1.34E-05
0.003663	2.09338	1.34E-05	1.34E-05
-0.00375	1.03409	1.40E-05	1.40E-05
0.003766	2.48511	1.42E-05	1.42E-05
0.003774	-0.1284	1.42E-05	1.42E-05
0.003784	4.81653	1.43E-05	1.43E-05
-0.00381	0.685965	1.45E-05	1.45E-05
0.003845	1.76904	1.48E-05	1.48E-05
0.003858	2.42627	1.49E-05	1.49E-05
0.004026	1.84202	1.62E-05	1.62E-05

The average value for Sphere objective function is $6.8 * 10^{-6}$. The value for GA is equivalent to $6.1 * 10^{-5}$ which is a bigger number than value obtained from NSGA-II. Therefore NSGA-II yielded a more accurate result.

4.4 NSGA-II and MATPOWER Implementation

The proposed program invokes a function which evaluates system variables, including voltage magnitudes and phase angles, using the MATPOWER 4.1 power flow (PF) [15]. The overall structure is shown in Figure 4.11.

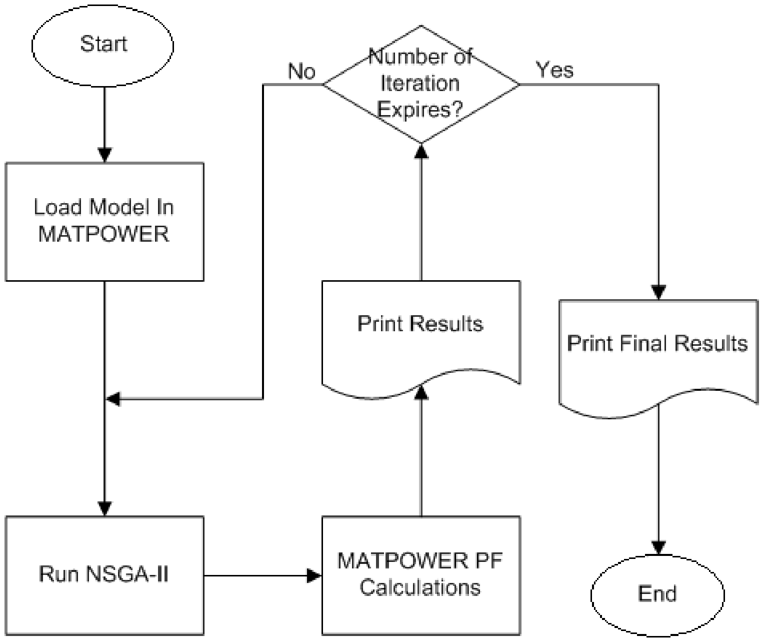

Figure 4.11 Flowchart of the proposed technique

4.4.1 Steps toward Building the Code

NSGA-II code is adopted from work done by Deb [55] written in MATLAB. Optimisation parameters such as number of design variables, number of objectives, number of constraints, should be specified in the NSGA-II optimisation options structure to solve the optimisation problem. The structure is created by function nsgaopt(). The objective function is created as an *.m file and specify the function handle options.objfun to this function.

4.4.2 First Step – Setting up Parameters

The optimization model specification is specified as Table 4.8.

Table 4.8 Specifying optimisation model in NSGA-II for a power system network

```
clc;
clear all;
close all;
options = nsgaopt();                     % create default options
options.popsize = 50;                    % population size
options.maxGen  = 50;                    %max generation
options.numObj = 2;                      % number of objectives
options.numVar = 4;                      % number of design variables
options.numCons = 0;                     % number of constraints
options.lb = [2 2 2 2];                  % lower bound of x1,x2,x3,x4
options.ub = [30 30 100 100];            % upper bound of x1,x2,x3,x4
options.objfun = @objfun;                % objective function
result = nsga2(options);                 % begin the optimization
```

In Table 4.8 four variables are defined. The first two variables are location of DG and the second two are the size of DG in MW. Upper and lower bound are specified with respect to the case of study. In a 30 bus case each of buses except the first bust (slack bus) are the candidates so the range of first and second variables are set from 2 to 30. The third and fourth variables range is [0,100] meaning that capacity of each DG could vary from none to 100 MW. As the location is a normal number not a real number, the integer code is set to 2 in options.vartype vector. At the start of the optimisation, uniform random population is initialised. Binary tournament selection and intermediate crossover are performed on variables. Crossover rate is 2 per number of variable. Mutation type is Gaussian which adds a normally distributed random number to each variable. Child and S are defined in equations (4-4) and (4-5) [55].

Child = Parent + S * Rand*(Ub-Lb) (4-4)

S = Scale*(1 - Shrink×CurrGen / MaxGen) (4-5)

where S is the deviation from the standard normal distribution. As the optimization progress proceeds, Shrink decreases the mutation range. Ub, Lb, CurrGen, and MaxGen represent upper bound, lower bound, current generation and maximum generation respectively.

4.4.3 Second Step - Creating Objective Functions

The objective function is specified by options.objfun parameter created by the function *nsgaopt().* Its prototype as shown in Table 4.2, 4.4 and 4.6 is depicted in Table 4.9

Table 4.9 Prototype of objective function creation in NSGA-II

```
[y, cons] = objfun(x, varvargin)
```

where x, y are defined as

x : Design variables vector, its length must equals options.numVar.

y : Objective values vector, its length must equals options.numObj.

cons variable is a vector defined for constraint violations. Its length must equals options.numCons. If there is no constraint, it returns empty vector. Any variable(s) which are passed to nsga2 function will be finally passed to this objective function. For example, if the line in Table 4.10 is called, the two addition parameter passed to nsga2 model and param will be passed to the objective function in Table 4.11.

Table 4.10 NSGA-II call function

```
result = nsga2(opt, model, param)
```

Table 4.11 Parameters pass from Table 4.10 to objective function

```
[y,const]=objfun(x, model, param)
```

Table 4.12 shows objective functions calls another function named as Raphson to do the power flow calculation.

Table 4.12 Calling power flow from MATPOWER

```
function [y, cons] = TP_Test_objfun(x)

y = [0,0];

cons = [];

[Vm, Pl,s,Ctotall,Sumfloww] = Raphson (x(1),x(2),x(3),x(4))
```

The objective functions calls another function named as Raphson to do the power flow calculation based on MATPOWER. In this function, x(1) and x(2) are the locations and x(3) and x(4) are the capacities. The return values from MATPOWER are Vm, Pl, S, Ctotall, Sumfloww. Vm is a vector of voltage magnitudes corresponding to nodes. Pl is the total real power loss of the system, Ctotall is the total cost of the added DG. Sumfloww is the real power flow associated with slack 1 (from bus 1 to bus 2 and 3 in 30 bus case for example). Objective could be chosen, altered or defined in this *.m file. For example adding average load voltage deviation in a 30 bus case Table 4.12 is completed as shown in table 4.13

Table 4.13 Calling power flow from MATPOWER with average load voltage deviation as the objective

```
function [y, cons] = TP_Test_objfun(x)

y = [0,0];

cons = [];

[Vm, Pl,s,Ctotall,Sumfloww] = Raphson (x(1),x(2),x(3),x(4))

ALVD=0;

for k=1:30

ALVD=(((1.060-Vm(k))/1.060).^2)+ALVD;

end
```

Vector of voltage shown as Vm are returned from the sub-function Raphson. Raphson sub-function is explained in Section 4.4.4.

Constraints are also defined here. In equations (4-1e) and (4-1f) an example is represented to show the constraints handling.

Objectives

$$f_1(x) = x_1 \tag{4-6}$$

$$f_2(x) = (1 + x_2)/x_1 \tag{4-7}$$

Design variables

$$x_1 \in [0.1, 1.0] \tag{4-8}$$

$$x_2 \in [0,5] \tag{4-9}$$

Constraints

$$g_1(x) = x_2 + 9x_1 \geq 6 \tag{4-10}$$

$$g_2(x) = -x_2 + 9x_1 \geq 1 \tag{4-11}$$

The constraint violation for the above optimisation problem is written as Table 4.14.

Table 4.14 Defining constraints in code for equations (4-10) and (4-11)

```
c = x(2) + 9*x(1) - 6;

if(c<0)

cons(1) = abs(c);

end

c = -x(2) + 9*x(1) - 1;

if(c<0)

cons(2) = abs(c);

end
```

Similarly if there are any constraints on the size or capacity of DG placed on a bus it can be defined as presented. For example consider the following constraints as (4-12), (4-13), and (4-14).

$$Bus\ 30 < 10\ MW \tag{4-12}$$

$$Bus\ 10 < 3\ MW \tag{4-13}$$

$$Total\ generation < 60\ MW \tag{4-14}$$

The applied code is defined as Table 4.15.

Table 4.15 Defining constraint in NSGA-II with respect to constraints of inequalities (4-12), (4-13) and (4-14)

```
c = 10-x(3);
            if (x(1)==30)&&(c<0)|| (x(2)==30)&&(c<0)
            cons(1) = abs(c);
            end
 c = 10-x(4);
            if (x(1)==30)&&(c<0)|| (x(2)==30)&&(c<0)
            cons(2) = abs(c);
            end
 c = 3-x(3);
            if (x(1)==10)&&(c<0)|| (x(2)==10)&&(c<0)
                  cons(3) = abs(c);
            end
   c = 3-x(4);
            if (x(1)==10)&&(c<0)|| (x(2)==10)&&(c<0)
            cons(4) = abs(c);
            end
 c = 60-x(3)-x(4);
            if (c<0)
      cons(5) = abs(c);
      end
```

4.4.4 Third Step – Power Flow Calculations

Loading the power system case is done in MATPOWER. Raphson sub-function invokes power flow (PF) for obtaining the value of variables to be passed to the second stage. Table 4-16 codes show the beginning of this sub-function.

Table 4.16 Loading power flow calculation by calling Raphson file and loading case 30 in MATPOWER

```
function [Vm,PI,S,Ctotal,Sumflow]=Raphson(n1,n2,m1,m2);

define_constants;

mpc=loadcase('case 30');

size(mpc.gen,1);
```

The sub-function loads case30 in MATPOWER [208]. The last line gives the last row of generator data. To add m capacity to bus n the code is Table 4.17.

Table 4.17 Adding m1 capacity to bus number n1

```
mpc.gen (n1,PG) = m1;
```

It means m1 MW is added to the bus located at row n1. If m1 is added to row 7 it means it is added to bus 7, hence the care has been taken to make sure the line and bus numbers corresponds to each other in the case.m file.
Similarly the same is done for the next added generators.
Runpf(mpc); executes the power flow which by MATPOWER default is set to Newton-Raphson. The code is shown in Table 4.18.

Table 4.18 Executing MATPOWER power flow

```
[MVAbase, bus, gen, branch, success, et]=runpf(mpc);

Vm=bus(:,8);

Losses=get_losses(MVAbase, bus, branch);
```

To get the losses, losses function is called and their real sum in calculated as shown in Table 4.19.

Table 4.19 Calculating the sum of real losses

```
Plvec=real(Losses);

Pl=sum(Plvec);
```

The cost of the DG is also a multiple of DG capacities represented in an hourly cost function. Hence it is coded as Table 4.20.

Table 4.20 Computing the investment and o&m cost

```
CinDG=(Cinv1*m1+Cinv2*m2)/(Adepr*8760);

ComDG=Com1*m1+Com2*m2;
```

Adepr is the inverse of levelized value which was discussed in the previous Chapter. The cost functions will be explained more extensively in the next Chapter.

4.5 Summary

In summary, this Chapter presents an in-depth insight into implementation of the methodology which is based on non-dominated sorting genetic algorithm II. This heuristic method of optimisation is adopted as it has been proved to be one of the efficient algorithms for solving single and multi-objective optimization techniques [209]. This Chapter explains how this optimisation method is implemented to solve the efficient planning of DGs in a power system network. MATPOWER which is package of *.m files for power flow calculation is used as a sub-function to the main optimisation engine. A more detailed discussion on GA and NSGA are presented in the beginning of the Chapter to show how elements of optimisation such as variables, objectives and constraints could be linked or redefined in our power system problem. Extracts of codes are included to illustrate the transition of the process. The coding process as a whole is divided into three stages, each stage dealing with one aspect of the optimisation. All in all, this Chapter attempts to translate the theories of optimisation and power system into one practical framework written in MATLAB.

Chapter 5

Results and Discussion

5.1 Introduction

In this chapter different test systems are applied to the proposed optimisation engine. Optimisation engine, as discussed in chapter 4, is a two stage hierarchy multi-objective programming based on Matlab. MATPOWER - Matlab cases are used as standard IEEE test systems. In order to obtain realistic results, the factors such as investment cost are updated based on the current market values. The objective and constraints are added one by one to facilitate the step by step analysis. The version of MATPOWER in optimisation attempts is 4.1. Matlab version used is 7.10 (R 2010 a). The cases are chosen from Mapower cases; however the codes have been modified in order to adapt it to the NSGA-II optimisation engine without changing the bus data. The attempt is to show the efficiency of the optimisation as well as its potential for applying the changes based on the view a planner takes. The cost penalty function as an example is introduced to manage the amount of power flow going to coming from the slack bus, hence creating less congestion on branches. The objectives are total network real loss and the cost of added DG. The cost of added DGs is divided into running and capital cost irrespective of type of DG. The cost is represented as an hourly function over a 5 year period hence the inflation is considered in the calculations. DGs are assumed to produce real power to the system. As the IEEE 14, 30 and 118 cases, which are used in the optimisation, belong to a Medium voltage range, the capacity quantities are in MW scale. Each of candidate DGs are capacities which could represent not solely a small DG but an array of DGs such as a wind farm. The power flow is based on AC Newton power flow.

5.2 IEEE -14 Bus Test System

This system consists of 4 generators, 11 loads and 20 branches. The total real load of the system is 259 MW. The schematic of the IEEE-14 bus test system illustrated in Figure 5.1.

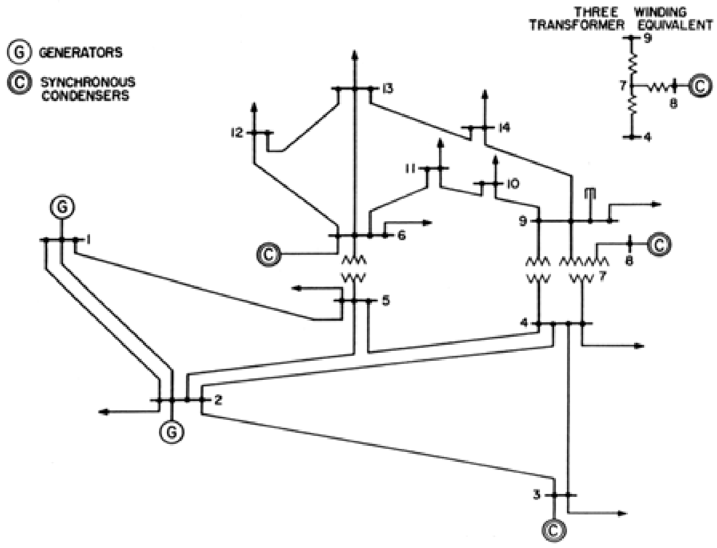

Figure 5.1 Single line representation of IEEE 14 test system used in the optimisation [210]

Table 5.1 shows the current active and reactive generation of the system in MW.

Table 5.1 Generation in IEEE 14 bus system

Bus Number	P_g (MW)	Q_g (MW)
1	232.4	-16.9
2	40	42.4
3	0	23.4
6	0	12.2
8	0	17.4

The complete data of IEEE 14 bus is presented in Appendix A.

To start with, two objectives are defined as such

1- Total function P_l and
2- Costs of the additional DG are defined as main objectives.

The first objective is the total real loss of the entire network. The cost is represented as hourly cost function. For every type of DG cost of investment calculated as the size of DG multiplied by its investment cost for 1 megawatt. Taking into account its levelized value over 5 years for long term studies [201], $C_{in\ DG}$ is represented as

$$C_{inDG} = \frac{C_{inv1} \times m_1 + C_{inv2} \times m_2}{Adepr \times 8760} \tag{5-1}$$

where m_1 m_2 are the sizes of first DG and second DG. C_{inv1} and C_{inv2} are the investment cost for the first and second DG (£/MW). C_{inv1} and C_{inv2} are assumed to be $5000(£/MW)$ and $C_{om\ DG}$ as $50\ (£/MW)$.

Inverse of levelized value is represented by $Adepr$ and is defined as

$$\frac{(1+d)^T - 1}{d(1+d)^T} \tag{5-2}$$

The discount rate represented by *d* is the expected rate of reduction in value from year to year [201] and T is the future time. Operation and maintenance (O & M) cost is normally assumed 1% of initial installed cost. The design variables are restricted to 2 to 14 for the buses and 0 to 50 MW for the potential DG capacities.

The result of first multi-objective optimisation is illustrated in Figure 5.2.

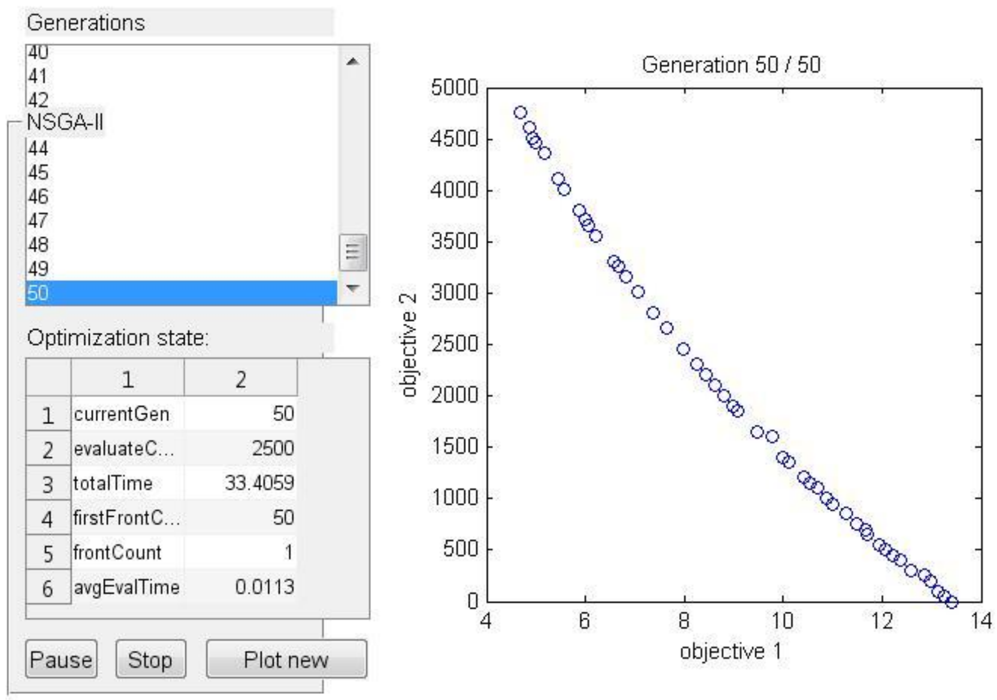

Figure 5.2 Bi-dimensional Pareto front of IEEE 14 bus for first objective as network real loss and second objective as hourly cost of candidate capacities for the maximum capacity of 50 MW

The total operation time is less than 34 second on Intel core i7 620 M at 2.67 GHz. The bi-dimensional space is due to two objective definitions. The first objective is represented in MW.

The population data is represented in Table 5.2.

Table 5.2 Population data of Figure 5.2

Row	1st bus	2nd bus	Capacity 1 (MW)	Capacity (MW)	Obj1	Obj2
1	8	3	50	45	4.67479	4764.3
2	8	3	0	0	13.3933	0
3	8	3	0	0	13.3933	0
4	3	8	47	24	6.20697	3560.69
5	6	3	0	33	9.47018	1654.97
6	6	3	8	24	9.76525	1604.82
7	3	8	50	30	5.56698	4012.05
8	8	3	31	45	5.86101	3811.44
9	6	3	0	37	9.07493	1855.57
10	6	3	2	15	11.2855	852.56
11	3	8	50	10	7.05605	3009.03

12	8	3	8	48	7.38165	2808.43
13	8	3	1	27	9.99643	1404.22
14	8	3	0	24	10.422	1203.61
15	8	3	1	26	10.1039	1354.07
16	6	3	0	6	12.5905	300.903
17	3	8	50	32	5.43336	4112.35
18	3	8	44	0	8.42396	2206.63
19	6	3	0	11	11.9523	551.656
20	8	3	2	6	12.3743	401.205
21	6	3	2	20	10.7009	1103.31
22	3	8	0	5	12.8444	250.753
23	6	3	0	20	10.8732	1003.01
24	8	3	0	2	13.1212	100.301
25	8	3	0	40	8.78963	2006.02
26	6	3	3	1	12.9773	200.602
27	8	3	48	44	4.85624	4613.85
28	8	3	0	13	11.7047	651.957
29	8	3	1	45	8.24463	2306.93
30	8	3	21	45	6.58499	3309.94
31	3	8	50	39	4.98727	4463.4
32	3	8	45	4	7.97739	2457.38
33	8	3	10	43	7.63222	2657.98
34	8	3	46	41	5.18609	4363.1
35	3	8	50	13	6.81477	3159.49
36	8	3	21	44	6.66458	3259.79
37	3	8	48	25	6.0596	3660.99
38	8	3	1	8	12.2243	451.355
39	3	8	50	24	5.98438	3711.14
40	8	3	21	45	6.58499	3309.94
41	6	3	0	23	10.5332	1153.46
42	8	3	0	1	13.2567	50.1506
43	8	3	0	10	12.0777	501.506
44	3	8	50	40	4.92627	4513.55
45	3	4	13	1	11.6769	702.108
46	8	3	0	19	10.9887	952.861
47	6	3	0	38	8.97877	1905.72
48	8	3	0	42	8.60469	2106.32
49	6	3	1	14	11.4938	752.259
50	8	3	0	42	8.60469	2106.32

It must be noted that in a multi-objective optimisation, there is no preference over the contradictory objectives, so in planner views, each of the results in table 5.2 could be chosen. In our case, as the weights of significance of objectives are equal, the middle point or knee point is chosen as the compromised result. The row number 25 and 50 of Table 5.2 shows that the third bus is the optimised location with the capacity of 40 MW. The compromised results is also could be perceived by the frequency of bus number. Bus number 8 and 6 are the other alternatives for the loss reduction. If the planner decides get less real loss at the cost of more investment, row number 4 states that a DG equal to the capacity of 24 MW should be connected to the bus. In order to compare the loss before and after, 40 MW of capacity is added to the third bus and Power flow is run. The snapshot of the result is illustrated in Figure 5.3.

Branch Data								
Brnch #	From Bus	To Bus	From Bus Injection P (MW)	Q (MVAr)	To Bus Injection P (MW)	Q (MVAr)	Loss (I^2 * Z) P (MW)	Q (MVAr)
1	1	2	123.53	-12.27	-120.88	14.50	2.647	8.08
2	1	5	64.26	4.63	-62.25	-1.65	2.012	8.31
3	2	3	49.98	6.38	-48.87	-6.33	1.108	4.67
4	2	4	50.40	-0.43	-49.04	0.92	1.353	4.10
5	2	5	38.81	1.47	-38.01	-2.74	0.791	2.42
6	3	4	-5.33	-3.31	5.35	2.05	0.023	0.06
7	4	5	-49.07	10.95	49.39	-9.93	0.326	1.03
8	4	7	28.59	-9.61	-28.59	11.36	0.000	1.76
9	4	9	16.37	-0.42	-16.37	1.77	0.000	1.35
10	5	6	43.27	12.72	-43.27	-8.44	0.000	4.28
11	6	11	6.85	3.66	-6.80	-3.56	0.050	0.10
12	6	12	7.72	2.53	-7.65	-2.38	0.071	0.15
13	6	13	17.49	7.26	-17.28	-6.86	0.207	0.41
14	7	8	0.00	-16.99	-0.00	17.44	0.000	0.45
15	7	9	28.59	5.63	-28.59	-4.80	0.000	0.83
16	9	10	5.72	4.10	-5.71	-4.07	0.014	0.04
17	9	14	9.74	3.53	-9.62	-3.27	0.122	0.26
18	10	11	-3.29	-1.73	3.30	1.76	0.010	0.02
19	12	13	1.55	0.78	-1.55	-0.77	0.006	0.01
20	13	14	5.33	1.83	-5.28	-1.73	0.049	0.10
						Total:	8.790	38.41

Figure. 5.3 Power flow result of IEEE 14 bus system with the new 40 MW DG added to bus number 3

The initial total power loss is 13.937 MW.

5.3 Line Current Magnitude Constraints

All power system operators ensure their system adhere to thermal limits on transmission lines in order to avoid line deformation. Also, thermal limits are used as surrogates for voltage stability. The IEEE test problems do not include data on these limits [211]. In order to get a feasible solution high limits of thermal limits on IEEE 14 bus system are assumed 50 MW in [208,209]. To decrease the line congestion the capacities limits could be varied. In the first attempt capacity limits are set to maximum of 20 MW. The Figure 5.4 illustrates the Pareto front.

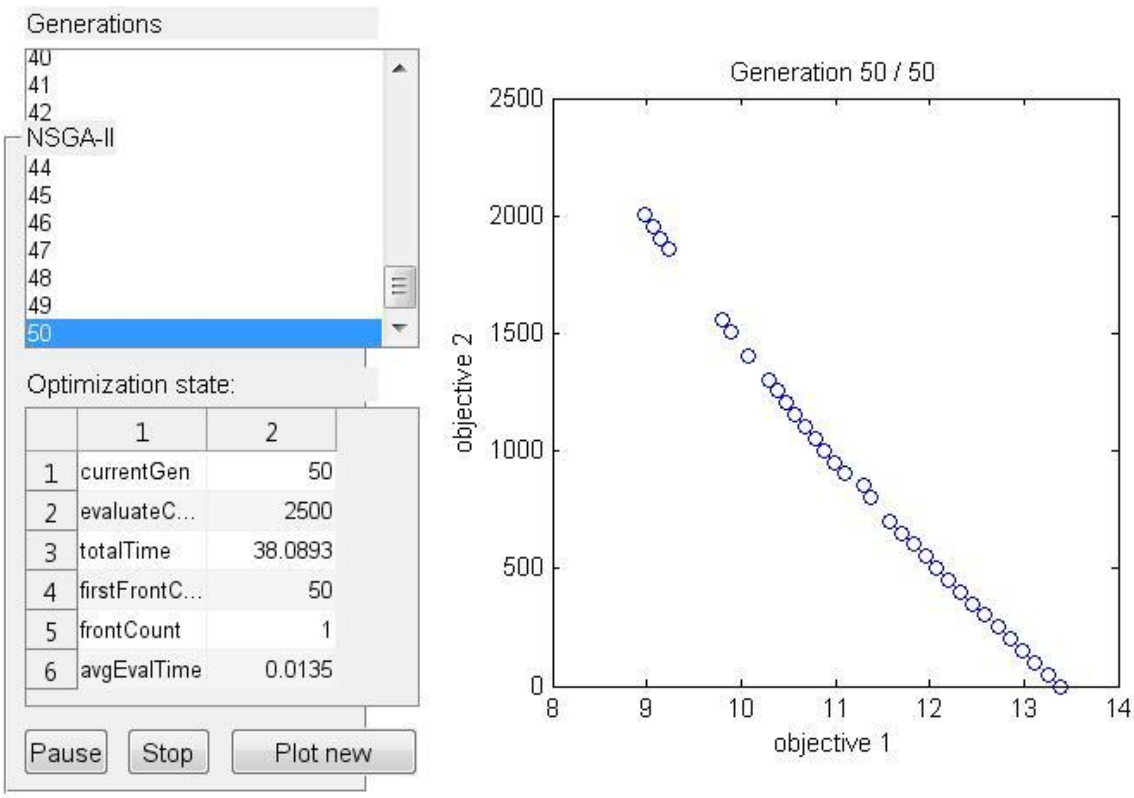

Figure 5.4 Bi-dimensional Pareto front of IEEE 14 bus for first objective as network real loss and second objective as hourly cost of candidate capacities for the maximum capacity of 20 MW

It could be noted that the knee point gives one DG connected to bus 3 with the capacity of 19 MW (row number 8 in Table 5.3). Hence we apply the constraints on the capacity to observe the outcome on line congestion. Running the power flow with the new capacity on the third bus is illustrated in Figure 5.5

Brnch #	From Bus	To Bus	From Bus Injection P (MW)	Q (MVAr)	To Bus Injection P (MW)	Q (MVAr)	Loss (I^2 * Z) P (MW)	Q (MVAr)
1	1	2	140.87	-16.58	-137.42	21.28	3.455	10.55
2	1	5	70.12	4.17	-67.73	0.36	2.387	9.85
3	2	3	62.12	4.77	-60.44	-2.31	1.683	7.09
4	2	4	53.38	-1.05	-51.87	2.04	1.517	4.60
5	2	5	40.21	1.29	-39.37	-2.38	0.849	2.59
6	3	4	-14.76	0.65	14.91	-1.60	0.144	0.37
7	4	5	-55.38	13.51	55.80	-12.19	0.419	1.32
8	4	7	28.32	-9.63	-28.32	11.36	0.000	1.73
9	4	9	16.22	-0.42	-16.22	1.74	0.000	1.33
10	5	6	43.69	12.61	-43.69	-8.26	0.000	4.35
11	6	11	7.11	3.60	-7.06	-3.49	0.053	0.11
12	6	12	7.76	2.51	-7.68	-2.37	0.071	0.15
13	6	13	17.62	7.24	-17.42	-6.82	0.210	0.41
14	7	8	0.00	-17.07	-0.00	17.52	0.000	0.46
15	7	9	28.32	5.71	-28.32	-4.89	0.000	0.81
16	9	10	5.46	4.17	-5.45	-4.13	0.013	0.04
17	9	14	9.58	3.58	-9.46	-3.32	0.119	0.25
18	10	11	-3.55	-1.67	3.56	1.69	0.011	0.03
19	12	13	1.58	0.77	-1.58	-0.76	0.006	0.01
20	13	14	5.49	1.78	-5.44	-1.68	0.052	0.11
						Total:	10.989	46.15

Figure 5.5 Power flow of IEEE 14 bus with 19 MW DG on the third bus

As Figure 5.5 illustrates the congestion on most lines are increased. This is due to the high demand in bus number 2 (P_d= 21.7 MW , Q_d =12.7 MVAr) and 3 (P_d= 94.2 MW , Q_d =19 MVAr). The optimisation engine has to converge subject to equality constraints. Hence the power flow is compensated from the slack bus. The increase in line congestion in two different cases of added 19 MW DG and 40 MW DG to bus number 3 is illustrated in Figure 5.6.

Branch Data for addidional 19 MW DG

Brnch #	From Bus	To Bus	From Bus P (MW)
1	1	2	140.87
2	1	5	70.12
3	2	3	62.12
4	2	4	53.38
5	2	5	40.21
6	3	4	-14.76
7	4	5	-55.38
8	4	7	28.32
9	4	9	16.22
10	5	6	43.69
11	6	11	7.11
12	6	12	7.76
13	6	13	17.62
14	7	8	0.00
15	7	9	28.32
16	9	10	5.46
17	9	14	9.58
18	10	11	-3.55
19	12	13	1.58
20	13	14	5.49

Branch Data for addidional 40 MW DG

Brnch #	From Bus	To Bus	From Bus P (MW)
1	1	2	123.53
2	1	5	64.26
3	2	3	49.98
4	2	4	50.40
5	2	5	38.81
6	3	4	-5.33
7	4	5	-49.07
8	4	7	28.59
9	4	9	16.37
10	5	6	43.27
11	6	11	6.85
12	6	12	7.72
13	6	13	17.49
14	7	8	0.00
15	7	9	28.59
16	9	10	5.72
17	9	14	9.74
18	10	11	-3.29
19	12	13	1.55
20	13	14	5.33

Figure 5.6 Branch flow comparison of two independent cases. One for additional 19MW and second for additional 40 MW on the bus number 3. Decreasing the introduced DG capacity doesn't help the line congestion problem.

Figure 5.6 shows that in a power system network arbitrary capacity manipulation on a pre-determined bus (here bus number 3), is not a robust solution for determining the size of a DG. In order to solve the issue, a penalty cost function is introduced in 5.4.

Comparing Figure 5.2 and 5.4, it is observed that the results also exist at the near bottom of the Figure 5.2 (line 46 of Table 5.2) which confirms the consistency of the optimisation. To get the total loss of 8.7 and hourly cost as 2006 (row 25 in table 5.2) in the second Pareto (Figure 5.4) .The population generated from Figure 5.4 is illustrated in Table 5.3.

Table 5.3 population generated from Figure 5.4

Row	1st bus	2nd bus	Capacity 1 (MW)	Capacity2 (MW)	Obj1	Obj2
1	3	8	0	0	13.3933	0
2	3	8	20	20	8.97558	2006.02

3	3	8	20	20	8.97558	2006.02
4	3	8	0	0	13.3933	0
5	3	8	14	0	11.5827	702.108
6	3	8	14	2	11.3741	802.409
7	3	8	18	0	11.1053	902.71
8	3	8	19	0	10.9887	952.861
9	3	8	19	7	10.2879	1303.91
10	3	8	19	2	10.7848	1053.16
11	3	8	20	11	9.79332	1554.67
12	3	8	20	4	10.4702	1203.61
13	3	8	19	6	10.3858	1253.76
14	3	8	20	17	9.24165	1855.57
15	3	8	20	18	9.15224	1905.72
16	3	8	20	19	9.06355	1955.87
17	3	8	20	8	10.079	1404.22
18	3	8	20	10	9.88781	1504.52
19	3	8	12	5	11.3074	852.56
20	3	8	20	10	9.88781	1504.52
21	3	8	20	8	10.079	1404.22
22	3	8	1	0	13.2567	50.1506
23	3	8	2	0	13.1212	100.301
24	3	8	1	0	13.2567	50.1506
25	3	8	3	0	12.9868	150.452
26	3	8	2	0	13.1212	100.301
27	3	8	4	0	12.8536	200.602
28	3	8	3	0	12.9868	150.452
29	3	8	5	0	12.7215	250.753
30	3	8	4	0	12.8536	200.602
31	3	8	6	0	12.5905	300.903
32	3	8	5	0	12.7215	250.753
33	3	8	6	0	12.5905	300.903
34	3	8	7	0	12.4606	351.054
35	3	8	8	0	12.3318	401.205
36	3	8	7	0	12.4606	351.054
37	3	8	9	0	12.2042	451.355
38	3	8	8	0	12.3318	401.205
39	3	8	9	0	12.2042	451.355
40	3	8	10	0	12.0777	501.506
41	3	8	11	0	11.9523	551.656
42	3	8	10	0	12.0777	501.506
43	3	8	12	0	11.8279	601.807
44	3	8	11	0	11.9523	551.656
45	3	8	13	0	11.7047	651.957
46	3	8	12	0	11.8279	601.807
47	3	8	13	0	11.7047	651.957
48	3	8	20	0	10.8732	1003.01

49	3	8	20	3	10.5698	1153.46
50	3	8	19	3	10.6839	1103.31

The result of the second row of Table 5.3 is very close to knee point of Figure 5.2 (row 25 of Table 5.2) but it offers two DG at buses 3 and 8 equal to 20 MW. As of Figure 5.2 it could be observed that the frequency of 8 was more than any other candidate buses .This is corroborated when tighter line limits is applied. If the planner decision allows the cost to go up to 2000 £/MWhour then the beginning of Pareto at the top (second row of Table 5.3) .Power flow is run with the two 20 MW added DG. The results are shown in Figure 5.7.

Branch Data								
Brnch #	From Bus	To Bus	From Bus Injection P (MW)	From Bus Injection Q (MVAr)	To Bus Injection P (MW)	To Bus Injection Q (MVAr)	Loss (I^2 * Z) P (MW)	Loss (I^2 * Z) Q (MVAr)
1	1	2	125.57	-12.79	-122.84	15.29	2.736	8.35
2	1	5	62.40	3.60	-60.51	-1.12	1.892	7.81
3	2	3	58.42	5.23	-56.93	-3.56	1.494	6.29
4	2	4	47.03	-1.67	-45.86	1.61	1.177	3.57
5	2	5	35.68	0.72	-35.01	-2.38	0.667	2.04
6	3	4	-17.27	-0.49	17.47	-0.33	0.196	0.50
7	4	5	-48.02	12.74	48.33	-11.75	0.316	1.00
8	4	7	15.69	-9.55	-15.69	10.20	0.000	0.65
9	4	9	12.92	-0.58	-12.92	1.41	0.000	0.84
10	5	6	39.59	13.65	-39.59	-9.98	0.000	3.67
11	6	11	4.61	3.91	-4.58	-3.84	0.030	0.06
12	6	12	7.44	2.60	-7.37	-2.46	0.067	0.14
13	6	13	16.34	7.36	-16.15	-7.00	0.186	0.37
14	7	8	-20.00	-15.30	20.00	16.29	0.000	0.99
15	7	9	35.69	5.11	-35.69	-3.84	0.000	1.26
16	9	10	7.94	3.83	-7.92	-3.77	0.022	0.06
17	9	14	11.17	3.33	-11.01	-3.01	0.154	0.33
18	10	11	-1.08	-2.03	1.08	2.04	0.004	0.01
19	12	13	1.27	0.86	-1.27	-0.86	0.005	0.00
20	13	14	3.92	2.05	-3.89	-1.99	0.030	0.06
						Total:	8.976	37.99

Figure 5.7 Power flow result of IEEE 14 bus system with two new 20 MW DGs added to bus number 3 and 8

5.4 Slack bus Penalty Function

Slack Bus provides or absorbs active/reactive power from the system in order to maintain power flow equality constraints. In the case of big loads it has to import power from the network. If DGs are chosen big enough the effect could be reversed; however as it was shown in 5.3 the congestion problem is not necessarily solved. Optimising power flow (OPF) which was discussed in chapter 3 by numerical means have been utilised but convergence is still an issue since value of the converged load flow Jacobian could become singular [212]. As the multi-objective introduced NSGA-II optimisation is keeping the defined objectives (in our case, cost and real power flow), a penalty function on the cost could shift the optimisation point to a less import or export of power flow from the slack bus. The proposed function is defined as

$$\begin{cases} C_{supslack} = e^{(0.0461 * sumflow)} \; if \; sumflow \geq 0 \\ C_{supslack} = e^{-(0.0461 * sumflow)} \; if \; sumflow < 0 \end{cases} \tag{5-3}$$

$$sumflow = \sum_{i=1}^{b} b_i \tag{5-4}$$

$C_{supslack}$ is the active power flow to or from the slack bus. $sumflow$ is the summation of branch power flows. The function is illustrated in Figure 5.8

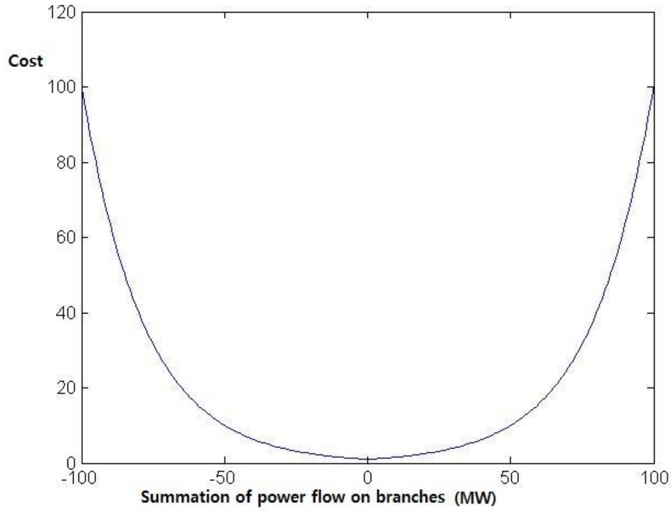

Figure 5.8 Penalty function defined to control the power flow on the slackbus

As 5.8 illustrates, the power flow from the point 50 MW is more heavily penalised. The reason is that 50 MW is considered the thermal constraints on branches.

The cost is then added to the cost of additional DGs. Therefore the new cost for the objective function is defined as

$$C_{Total} = C_{in\ DG} + C_{om\ DG} + C_{supslack} \tag{5-5}$$

where $C_{in\ DG}$ is the initial cost and $C_{om\ DG}$ is the running cost of DGs.

5.5 Running the Optimisation with the Additional Penalty Function

In a nutshell, the purpose of introducing the penalty function was to reduce the congestion on the lines. In order to run the power flow with the new values, it is required to obtain the new capacity and location of the IEEE 14.

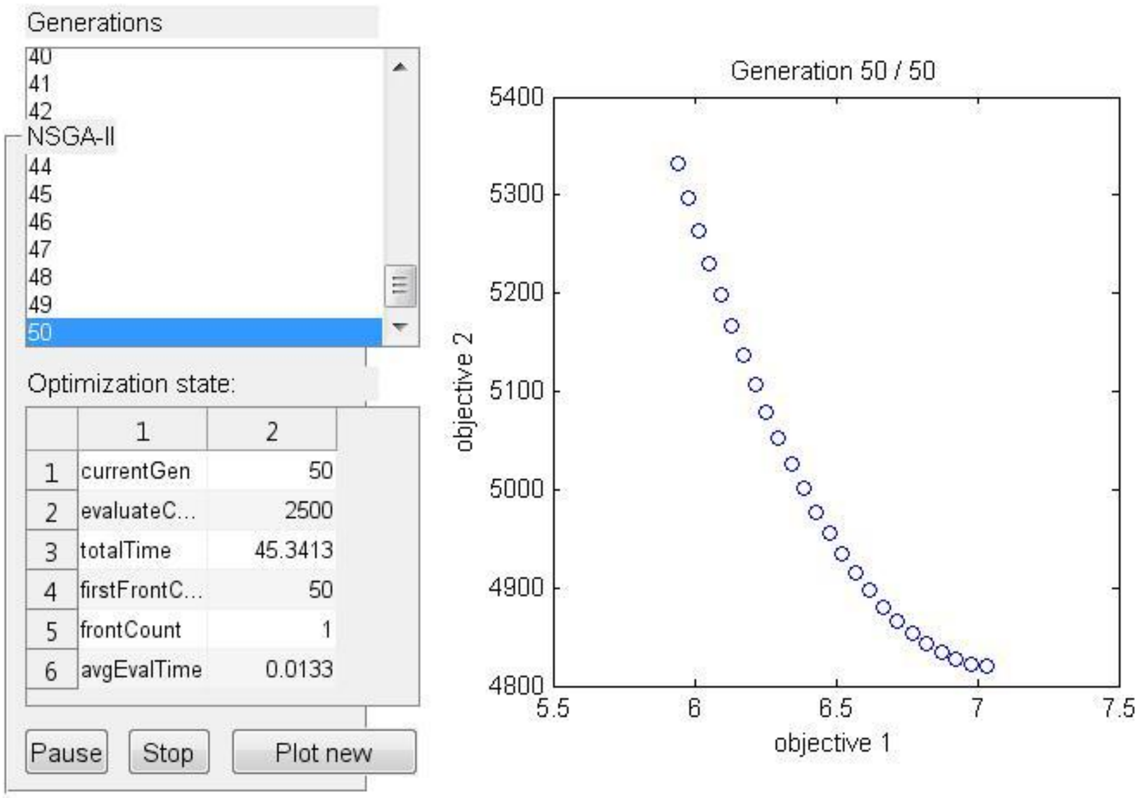

Figure 5.9 Pareto front with the cost penalty function

The generated population of Figure 5.9 is illustrated in Table 5.4

Table 5.4 population generated from Figure 5.9

Row	1st Bus	2nd Bus	Capacity 1 (MW)	Capacity 2 (MW)	Obj 1	Obj 2
1	8	6	50	50	5.94164	5332.34
2	6	8	26	50	7.03327	4820.26
3	8	6	50	26	7.03327	4820.26
4	8	6	50	50	5.94164	5332.34
5	8	6	50	49	5.97824	5297.72
6	8	6	50	48	6.01561	5263.88
7	8	6	50	47	6.05374	5230.84
8	8	6	50	49	5.97824	5297.72
9	8	6	50	46	6.09264	5198.66
10	8	6	50	48	6.01561	5263.88
11	8	6	50	45	6.1323	5167.37
12	8	6	50	47	6.05374	5230.84
13	8	6	50	44	6.17273	5137.02
14	8	6	50	46	6.09264	5198.66
15	8	6	50	43	6.21394	5107.66
16	8	6	50	45	6.1323	5167.37
17	8	6	50	42	6.25591	5079.35

18	8	6	50	44	6.17273	5137.02
19	8	6	50	43	6.21394	5107.66
20	8	6	50	41	6.29866	5052.12
21	8	6	50	42	6.25591	5079.35
22	8	6	50	40	6.34218	5026.04
23	8	6	50	41	6.29866	5052.12
24	8	6	50	39	6.38647	5001.16
25	8	6	50	40	6.34218	5026.04
26	8	6	50	38	6.43154	4977.55
27	8	6	50	39	6.38647	5001.16
28	8	6	50	37	6.47739	4955.28
29	8	6	50	38	6.43154	4977.55
30	8	6	50	36	6.52401	4934.4
31	8	6	50	37	6.47739	4955.28
32	8	6	50	35	6.57142	4914.99
33	8	6	50	36	6.52401	4934.4
34	8	6	50	34	6.6196	4897.13
35	8	6	50	35	6.57142	4914.99
36	8	6	50	33	6.66856	4880.89
37	8	6	50	34	6.6196	4897.13
38	6	8	32	50	6.71831	4866.36
39	8	6	50	33	6.66856	4880.89
40	8	6	50	31	6.76884	4853.63
41	6	8	32	50	6.71831	4866.36
42	8	6	50	30	6.82015	4842.78
43	8	6	50	31	6.76884	4853.63
44	8	6	50	29	6.87225	4833.91
45	8	6	50	30	6.82015	4842.78
46	8	6	50	28	6.92513	4827.13
47	8	6	50	29	6.87225	4833.91
48	8	6	50	27	6.9788	4822.54
49	8	6	50	28	6.92513	4827.13
50	8	6	50	27	6.9788	4822.54

As the results in Table 5.4 indicate, bus number 3 is no longer recognized as the optimum place for DGs, although the biggest load is located at this bus. Buses number 6 and 8 are the optimum locations and the knee point on the Pareto (row 20), suggest two DG with capacity of 50 and 41 on bus 8 and 6 respectively. The capacities are added to and power flow is run to investigate the congestion on branches.

Branch Data								
Brnch #	From Bus	To Bus	From Bus Injection P (MW)	Q (MVAr)	To Bus Injection P (MW)	Q (MVAr)	Loss (I^2 * Z) P (MW)	Q (MVAr)
1	1	2	93.51	-4.36	-92.00	3.12	1.509	4.61
2	1	5	40.79	2.46	-39.98	-4.49	0.813	3.36
3	2	3	60.40	4.98	-58.80	-2.90	1.593	6.71
4	2	4	30.36	-2.20	-29.87	0.03	0.491	1.49
5	2	5	19.54	0.07	-19.34	-3.18	0.201	0.61
6	3	4	-35.40	2.52	36.23	-1.74	0.830	2.12
7	4	5	-45.60	11.02	45.87	-10.15	0.277	0.87
8	4	7	-11.70	-6.09	11.70	6.42	0.000	0.33
9	4	9	3.14	0.68	-3.14	-0.63	0.000	0.05
10	5	6	5.84	16.22	-5.84	-15.60	0.000	0.61
11	6	11	9.07	2.06	-9.00	-1.91	0.072	0.15
12	6	12	7.97	2.28	-7.89	-2.12	0.074	0.15
13	6	13	18.61	6.46	-18.38	-6.02	0.224	0.44
14	7	8	-50.00	-12.93	50.00	17.07	0.000	4.14
15	7	9	38.30	6.51	-38.30	-5.05	0.000	1.46
16	9	10	3.54	5.78	-3.53	-5.75	0.013	0.03
17	9	14	8.41	4.63	-8.30	-4.41	0.104	0.22
18	10	11	-5.47	-0.05	5.50	0.11	0.022	0.05
19	12	13	1.79	0.52	-1.79	-0.52	0.007	0.01
20	13	14	6.67	0.74	-6.60	-0.59	0.070	0.14
						Total:	6.299	27.56

Figure 5.10 Power flow results of IEEE 14 with the added penalty function

Comparing Figure 5.10 and 5.6, shows there is significant reduction on the dependency of network on the slack bus. Furthermore, expect for the substation and bus number 3, all other buses adhere to the 50 MW limit. Although the added capacity is 51 MW more than 40 MW case (128% capacity increase), the improvement on the congested buses 1, 2, 4, 5 and 7 is significant. The reason is the introduction of penalty cost function which prefers bus 6 over 3 as the best location.

5.6 Optimisation of IEEE 30 Bus System

In order to verify the results from previous section, the optimisation is run for IEEE 30 bus system. This system consists of 6 generators, 21 loads, and 41 branches with total load of 283.4 MW.

The schematic of the IEEE-14 bus test system illustrated in Figure 5.11.

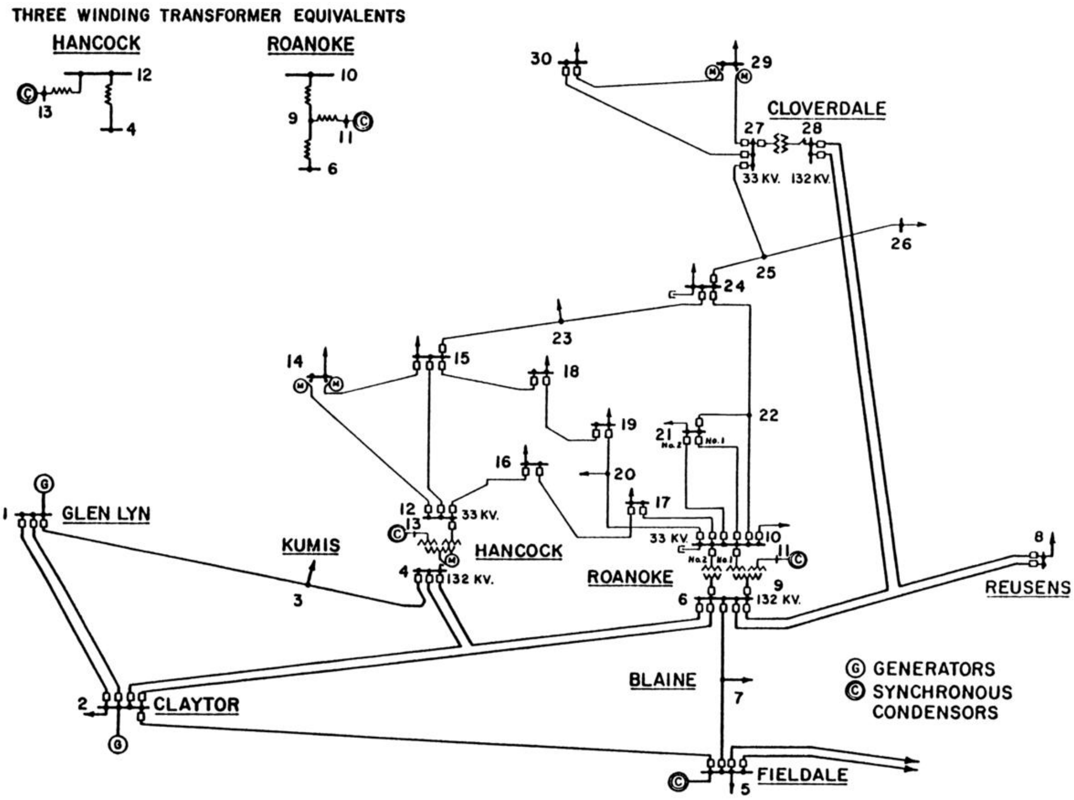

Figure 5.11 Single line representation of IEEE 30 test system used in the optimisation [210]

Table 5.5 shows the current active and reactive generation of the system in MW.

Table 5.5 Bus generation data of IEEE 30 bus system

Bus Number	P_g (MW)	Q_g (MW)
1	23.54	0
2	60.97	0
22	21.59	0
27	26.91	0
23	19.2	0
13	37	0

The complete data of IEEE 30 bus is presented in Appendix B.

Objectives functions are defined as total real power loss and cost of DGs. The location upper and lower band is set to [2 (two), 30 (thirty)]. Other parameters of optimisation such as number of iteration remain the same. Having run the optimisation, the proposed optimised locations are bus number 8 and 19. The simulation time remains fast at 49.33 seconds .The Pareto front is illustrated in Figure 5.12

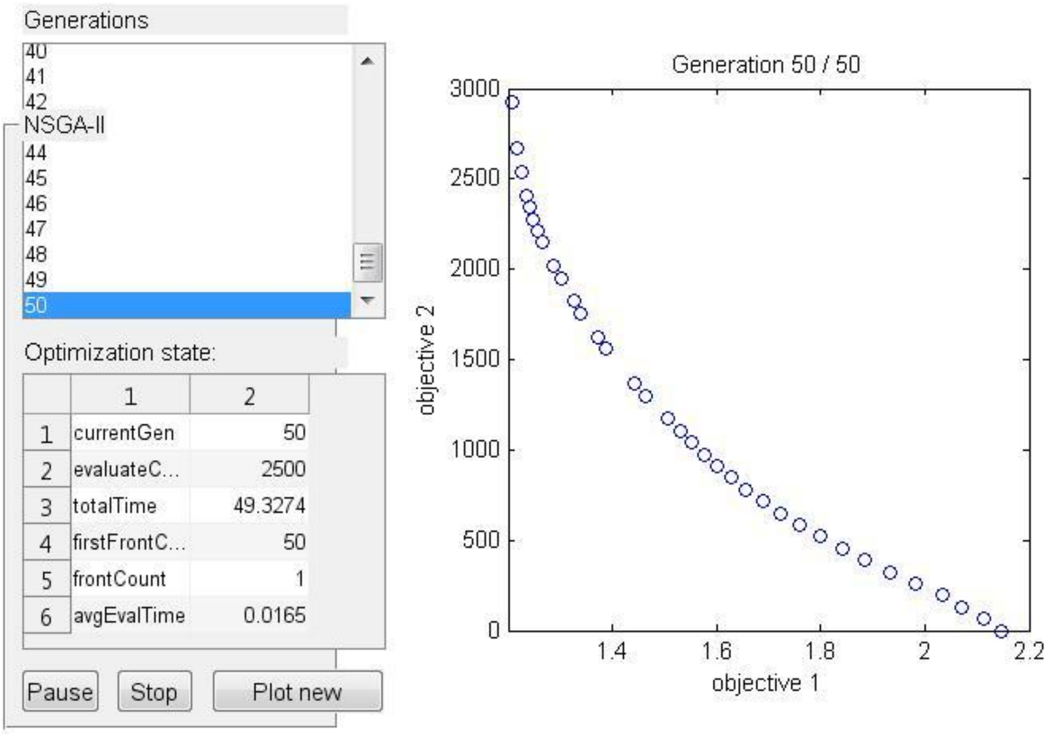

Figure 5.12 Pareto front of IEEE 30 bus system for cost and total real network loss

Table 5.6 shows the population data of Figure 5.12.

Table 5.6 The population data generated from 5.12

Row	Bus 1	Bus 2	Capacity 1 (MW)	Capacity 2 (MW)	Obj 1	Obj 2
1	8	19	28	17	1.20878	2927.56
2	12	8	0	0	2.14668	0
3	12	8	0	0	2.14668	0
4	8	19	10	14	1.38811	1561.37
5	19	8	4	0	1.9824	260.228
6	19	8	3	0	2.03509	195.171
7	8	19	12	15	1.33964	1756.54
8	8	19	0	12	1.65694	780.683
9	8	19	13	15	1.32537	1821.59
10	8	19	16	14	1.30133	1951.71
11	8	19	26	15	1.21756	2667.33

12	8	19	16	15	1.2877	2016.76
13	8	19	0	14	1.60189	910.797
14	8	19	18	15	1.26687	2146.88
15	8	19	2	15	1.5298	1105.97
16	8	19	1	15	1.55359	1040.91
17	8	19	4	14	1.50595	1171.02
18	8	19	7	14	1.44313	1366.2
19	8	19	7	13	1.46494	1301.14
20	8	19	20	17	1.23476	2407.11
21	8	19	7	14	1.44313	1366.2
22	19	8	5	0	1.9324	325.285
23	19	8	5	0	1.9324	325.285
24	19	8	6	0	1.88508	390.342
25	19	8	6	0	1.88508	390.342
26	19	8	7	0	1.84044	455.399
27	19	8	8	0	1.79845	520.455
28	19	8	7	0	1.84044	455.399
29	17	8	2	0	2.0715	130.114
30	12	8	0	1	2.11256	65.0569
31	19	8	9	0	1.75912	585.512
32	19	8	8	0	1.79845	520.455
33	8	19	19	15	1.25773	2211.94
34	8	19	9	16	1.37219	1626.42
35	8	19	0	9	1.75912	585.512
36	19	8	10	0	1.72244	650.569
37	8	19	19	16	1.24851	2276.99
38	17	8	2	0	2.0715	130.114
39	8	19	21	15	1.24201	2342.05
40	12	8	0	1	2.11256	65.0569
41	19	8	11	0	1.68838	715.626
42	19	8	10	0	1.72244	650.569
43	8	19	9	16	1.37219	1626.42
44	8	19	0	11	1.68838	715.626
45	8	19	24	15	1.2248	2537.22
46	19	8	13	0	1.62812	845.74
47	8	19	24	15	1.2248	2537.22
48	8	19	0	13	1.62812	845.74
49	8	19	1	14	1.5766	975.854
50	8	19	1	14	1.5766	975.854

The knee point or the trade-off point suggests 14 MW for bus number 19.The loss has been reduced to 1.893 MW from the initial 2.444 MW. Figure 5.13 shows power flow results of the additional 14 MW on bus 19.

Branch Data

Brnch #	From Bus	To Bus	From Bus Injection P (MW)	From Bus Injection Q (MVAr)	To Bus Injection P (MW)	To Bus Injection Q (MVAr)	Loss (I^2 * Z) P (MW)	Loss (I^2 * Z) Q (MVAr)
1	1	2	1.52	-2.00	-1.52	-0.99	0.001	0.00
2	1	3	9.91	4.55	-9.84	-6.27	0.064	0.24
3	2	4	12.55	5.35	-12.43	-6.98	0.119	0.34
4	3	4	7.44	5.07	-7.43	-5.04	0.008	0.03
5	2	5	11.98	4.53	-11.90	-6.15	0.087	0.35
6	2	6	16.25	7.58	-16.05	-8.92	0.203	0.61
7	4	6	19.40	11.72	-19.35	-11.50	0.053	0.21
8	5	7	11.90	6.33	-11.80	-7.05	0.097	0.23
9	6	7	11.04	3.02	-11.00	-3.85	0.042	0.11
10	6	8	24.56	24.51	-24.44	-24.00	0.127	0.51
11	6	9	1.01	-3.05	-1.01	3.07	0.000	0.02
12	6	10	0.58	-1.74	-0.58	1.76	0.000	0.02
13	9	11	0.00	0.00	0.00	0.00	-0.000	0.00
14	9	10	1.01	-3.07	-1.01	3.08	0.000	0.01
15	4	12	-7.13	-1.30	7.13	1.44	0.000	0.14
16	12	13	-37.00	-9.27	37.00	11.37	0.000	2.10
17	12	14	4.39	1.10	-4.37	-1.05	0.025	0.05
18	12	15	5.53	-0.72	-5.51	0.76	0.022	0.04
19	12	16	8.74	-0.05	-8.67	0.21	0.071	0.16
20	14	15	-1.83	-0.55	1.84	0.56	0.008	0.01
21	16	17	5.17	-2.01	-5.15	2.07	0.026	0.06
22	15	18	3.44	0.76	-3.42	-0.74	0.014	0.03
23	18	19	0.22	-0.16	-0.22	0.16	0.000	0.00
24	19	20	4.72	-3.56	-4.71	3.59	0.011	0.03
25	10	20	-2.49	4.34	2.51	-4.29	0.023	0.05
26	10	17	3.88	7.94	-3.85	-7.87	0.024	0.06
27	10	21	-2.00	-11.02	2.04	11.11	0.039	0.09
28	10	22	-3.61	-8.10	3.67	8.22	0.057	0.12
29	21	22	-19.54	-22.31	19.63	22.49	0.089	0.18
30	15	23	-7.97	-4.58	8.06	4.76	0.088	0.18
31	22	24	-1.70	7.51	1.77	-7.40	0.071	0.11
32	23	24	7.94	0.48	-7.86	-0.31	0.082	0.17
33	24	25	-2.61	1.04	2.63	-1.02	0.015	0.03
34	25	26	3.55	2.37	-3.50	-2.30	0.046	0.07
35	25	27	-6.18	-1.35	6.22	1.44	0.045	0.09
36	28	27	-7.39	-5.60	7.39	5.96	0.000	0.36
37	27	29	6.17	1.68	-6.08	-1.51	0.090	0.17
38	27	30	7.12	1.67	-6.95	-1.35	0.171	0.32
39	29	30	3.68	0.61	-3.65	-0.55	0.035	0.07
40	8	28	-5.56	-6.00	5.60	4.24	0.037	0.12
41	6	28	-1.79	-2.31	1.79	1.36	0.001	0.00
						Total:	1.893	7.50

Figure 5.13 Power flow results of IEEE 30 with the additional 14 MW DG on bus 19

Figure 5.13 shows there is no significant congestion on branches. To verify the penalty function effects, the cost penalty function is applied and the Pareto front is obtained in Figure 5.14.

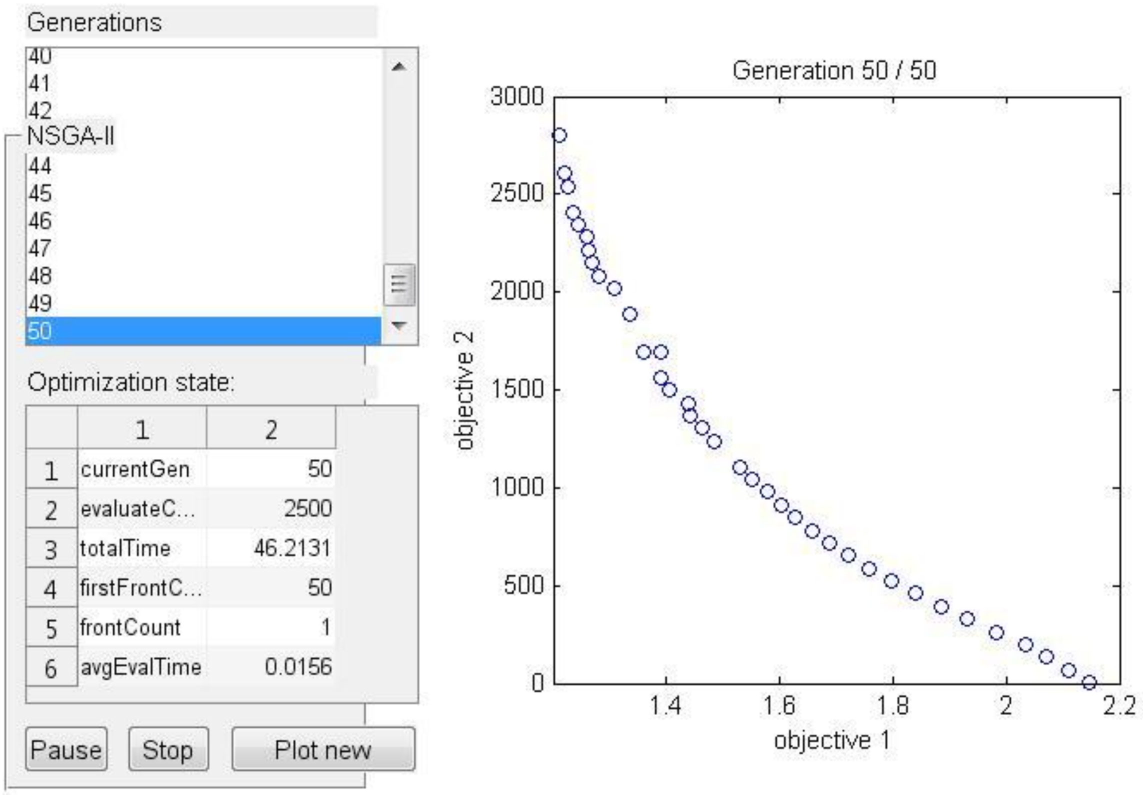

Figure 5.14 Pareto front of IEEE 30 bus system including the penalty function

Figure 5.14 results are very similar to 5.12 which didn’t have a penalty function. The reason is that, the line congestion does not exist on IEEE 30 hence, the there is no overly flow of power to be penalized. The population generated from Figure 5.14 is demonstrated in Table 5.7.

Table 5.7 Population data generated from 5.14

Row	1st Bus	2nd Bus	Capacity 1 (MW)	Capacity 2 (MW)	Obj 1	Obj2
1	12	8	0	0	2.14668	3.26642
2	19	8	17	26	1.21021	2799.77
3	12	8	0	0	2.14668	3.26642
4	20	8	14	15	1.33495	1887.86
5	19	8	14	5	1.48414	1237.4
6	19	8	13	13	1.3589	1692.53
7	20	8	15	16	1.30936	2018.09
8	8	10	0	1	2.11006	68.1709
9	19	8	12	0	1.65694	782.52
10	19	8	16	24	1.21864	2604.3
11	19	8	13	0	1.62812	847.492

12	19	8	14	0	1.60189	912.468
13	19	8	13	2	1.57714	977.448
14	19	8	14	2	1.55218	1042.43
15	19	8	15	8	1.40532	1497.4
16	19	8	15	22	1.23543	2408.86
17	19	8	15	24	1.2248	2539.15
18	19	8	11	11	1.43715	1432.4
19	20	8	11	15	1.39073	1692.53
20	19	8	14	18	1.27926	2083.21
21	19	8	4	0	1.9824	262.924
22	10	8	3	0	2.03389	198.001
23	19	8	5	0	1.9324	327.853
24	19	8	4	0	1.9824	262.924
25	19	8	14	7	1.44313	1367.4
26	19	8	6	0	1.88508	392.789
27	19	8	5	0	1.9324	327.853
28	19	8	14	3	1.52863	1107.42
29	19	8	14	22	1.24535	2343.73
30	19	8	7	0	1.84044	457.731
31	19	8	6	0	1.88508	392.789
32	19	8	14	3	1.52863	1107.42
33	19	8	8	0	1.79845	522.678
34	19	8	7	0	1.84044	457.731
35	19	8	9	0	1.75912	587.631
36	19	8	8	0	1.79845	522.678
37	19	8	19	16	1.25862	2278.59
38	10	8	2	0	2.07151	133.082
39	10	8	3	0	2.03389	198.001
40	10	8	2	0	2.07151	133.082
41	19	8	10	0	1.72244	652.589
42	19	8	9	0	1.75912	587.631
43	19	8	13	11	1.3908	1562.41
44	19	8	11	0	1.68838	717.552
45	19	8	10	0	1.72244	652.589
46	19	8	11	0	1.68838	717.552
47	19	8	18	16	1.2621	2213.46
48	19	8	15	5	1.46366	1302.4
49	19	8	15	5	1.46366	1302.4
50	19	8	17	16	1.2681	2148.34

Table 5.7 suggests bus 19 and 8 as the best locations. The trade-off point in row 12 is approximately the same as the results of Table 5.6 which would decrease the loss equivalent to 23 percent of its initial value.

5.7 Optimisation of IEEE 118 Bus System

In this stage a larger system is used for the optimisation and locating the size and site of two candidate DG with respect to their cost and the minimization of the real power loss. IEEE 118 bus system consists of 54 generators, 99 loads, and 186 branches with total load of 5677 MW. The full data of the network is presented in Appendix C.

The schematic of the IEEE-118 bus test system illustrated in Figure 5.15.

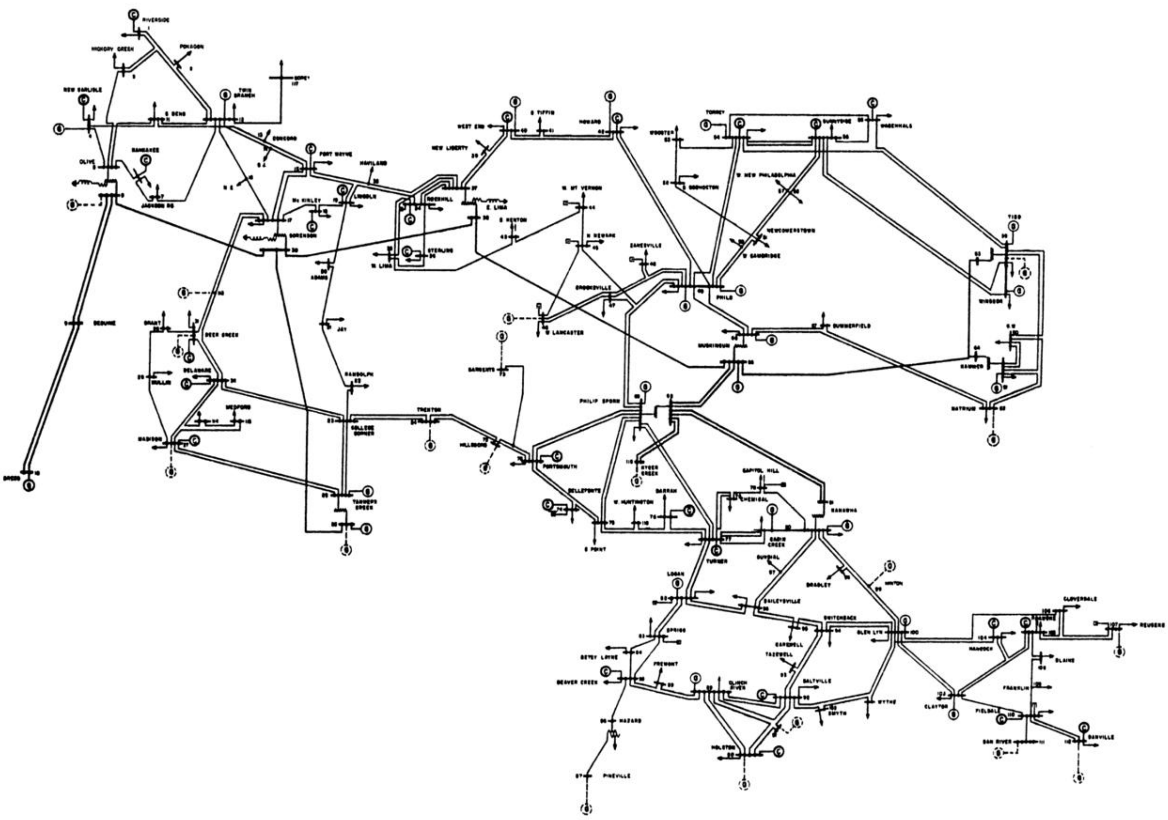

Figure 5.15 Single line representation of IEEE 118 test system used in the optimisation [210]

Table 5.8 shows the current active and reactive generation of the system in MW.

Table 5.8 IEEE 118 generation data

Bus Number	P_g (MW)	Q_g (MW)
10	450	0
12	85	0
25	220	0
26	314	0
31	7	0
46	19	0
49	204	0
54	48	0
59	155	0
61	160	0
65	391	0
66	392	0
69	516.4	0
80	477	0
87	4	0
89	607	0
100	252	0
103	40	0
111	36	0

Bus 69 is type 3 (slack bus). Running the power flow, the total loss is obtained as 132.863 MW. In order to find the best location and capacity, the optimisation is run. The maximum capacity of both DGs is kept at 50 MW. The Pareto front is illustrated in Figure 5.16.

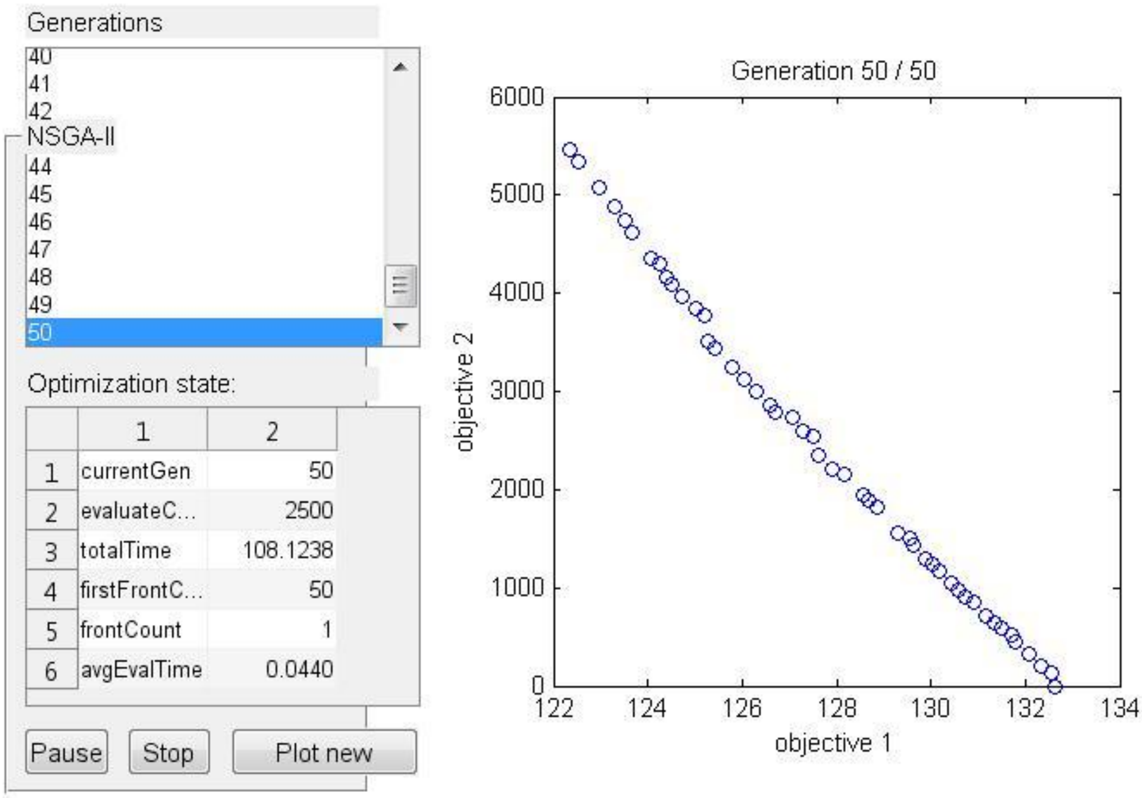

Figure 5.16 Pareto front of IEEE 118 bus system with 50 MW cap for each DG

The Pareto is not well distributed. Looking at the results in Table 5.9 makes it clearer.

Table 5.9 Population data corresponding to Figure 5.16

Row	1st bus	2nd bus	Capacity 1 (MW)	Capacity 2 (MW)	Obj 1	Obj 2
1	38	94	0	0	132.482	0
2	38	94	0	0	132.482	0
3	40	42	50	40	121.695	5855.12
4	40	112	50	33	122.119	5399.73
5	40	112	46	23	123.525	4488.93
6	40	112	50	22	123.161	4684.1
7	40	42	50	39	121.79	5790.07
8	63	40	0	4	132.05	260.228
9	40	42	48	28	123.09	4944.33
10	40	42	45	36	122.59	5269.61
11	40	42	45	34	122.791	5139.5
12	40	112	42	19	124.445	3968.47
13	40	112	37	6	126.742	2797.45
14	40	112	34	4	127.418	2472.16

15	38	40	0	25	129.083	1626.42
16	40	112	50	9	124.739	3838.36
17	40	42	38	11	126.139	3187.79
18	40	42	39	12	125.898	3317.9
19	55	112	2	9	131.293	715.626
20	40	42	41	12	125.66	3448.02
21	63	36	0	2	132.464	130.114
22	40	42	40	18	125.073	3773.3
23	38	112	0	6	131.722	390.342
24	40	112	44	2	126.467	2992.62
25	38	40	0	15	130.45	975.854
26	40	38	11	3	130.793	910.797
27	38	40	0	20	129.757	1301.14
28	38	40	0	22	129.485	1431.25
29	38	40	0	23	129.351	1496.31
30	38	40	0	27	128.819	1756.54
31	40	40	0	30	128.555	1951.71
32	63	42	1	8	131.456	585.512
33	40	112	44	10	125.318	3513.07
34	40	112	42	13	125.169	3578.13
35	40	112	48	18	123.84	4293.76
36	40	40	0	17	130.337	1105.97
37	40	42	29	18	126.395	3057.68
38	40	42	28	6	128.026	2211.94
39	38	40	1	17	130.097	1171.02
40	40	112	48	18	123.84	4293.76
41	40	42	34	7	127.128	2667.33
42	38	40	0	12	130.875	780.683
43	40	112	36	3	127.311	2537.22
44	38	40	0	32	128.17	2081.82
45	40	42	35	7	127.003	2732.39
46	42	40	4	4	131.668	520.455
47	38	40	0	31	128.298	2016.76
48	38	40	0	28	128.687	1821.59
49	40	112	47	16	124.194	4098.59
50	40	112	47	16	124.194	4098.59

The most frequent buses are bus number 40, 112, 42 and 38 with the frequency of 42, 17, 15 and 14 times which except for bus number 40, doesn’t yield a preference over other location. This is due to limit on the size of generators. In 5.6 the total real load is 283.4 and the capacity cap is assumed approximately 1/3 of the demand so 100 MW (50 MW each) is a realistic assumption as the DG penetration level is chosen up to 30% of the demand. In IEEE 118 the total real demand is 5677 MW hence the capacity limit of each DG should be increased. The limit is set to 500 MW for each and the simulation is run again. Figure 5.17 shows the Pareto result.

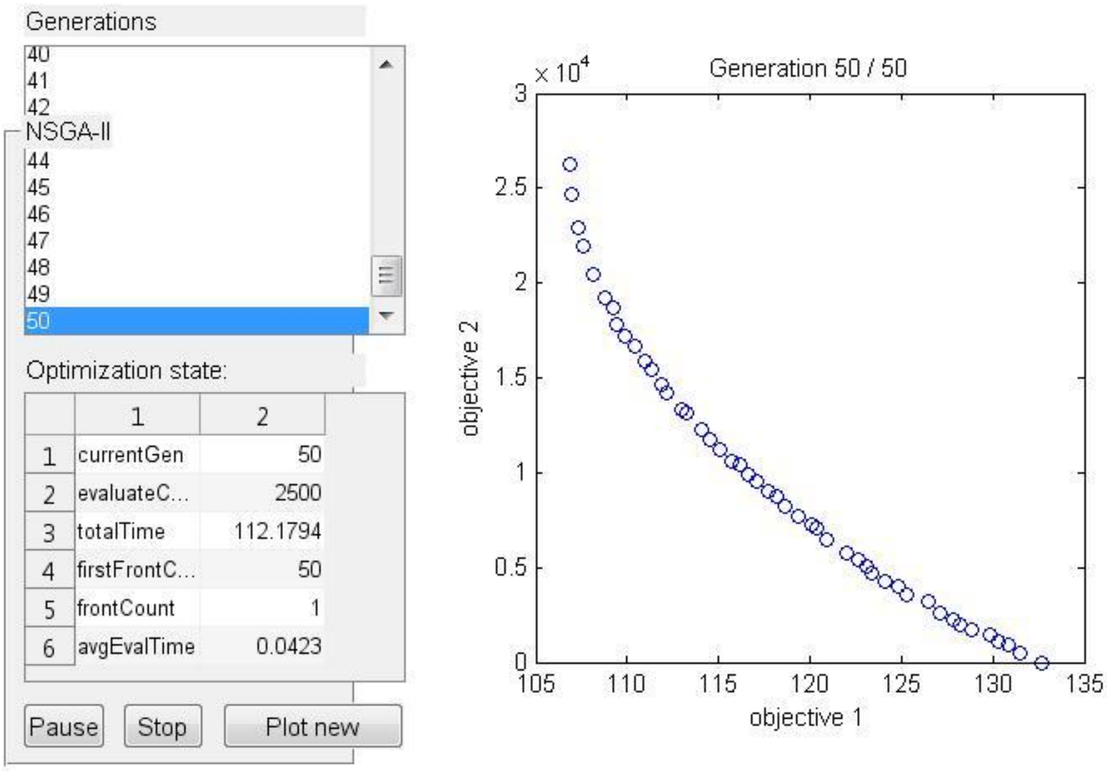

Figure 5.17 Pareto front of IEEE 118 bus system with 500 MW cap for each DG

As illustrated in 5.17, the distribution shows a drastic improvement. Looking at the population correspond to the Pareto in Table 5.10 the optimum location for the DGs are perceived.

Table 5.10 Population data corresponding to Figure 5.17

Row	1st bus	2nd bus	Capacity 1 (MW)	Capacity 2 (MW)	Obj 1	Obj 2
1	42	63	0	0	132.664	0
2	40	56	190	213	106.826	26217.9
3	42	63	0	0	132.664	0
4	40	56	152	162	108.134	20427.9
5	40	56	175	204	106.96	24656.6
6	40	56	89	11	120.951	6505.69
7	40	56	164	131	108.789	19191.8
8	41	38	49	0	126.501	3187.79
9	40	56	63	26	122.046	5790.07
10	40	56	126	62	114.041	12230.7

11	40	63	55	0	125.288	3578.13
12	40	56	116	140	110.382	16654.6
13	40	56	100	18	119.371	7676.72
14	40	56	132	86	112.169	14182.4
15	42	63	8	0	131.5	520.455
16	40	63	40	0	127.075	2602.28
17	40	56	87	39	118.605	8197.17
18	40	64	27	0	128.884	1756.54
19	40	63	66	0	124.082	4293.76
20	40	56	151	93	110.936	15873.9
21	40	56	132	73	112.973	13336.7
22	40	56	148	117	109.86	17240.1
23	40	56	142	132	109.459	17825.6
24	40	56	175	177	107.304	22900
25	40	51	22	0	129.886	1431.25
26	40	56	175	113	109.268	18736.4
27	40	56	61	0	124.814	3968.47
28	40	42	98	41	117.692	9042.91
29	40	56	92	71	115.732	10604.3
30	40	56	176	161	107.627	21924.2
31	40	42	56	17	123.417	4749.16
32	40	45	103	32	118.204	8782.69
33	40	63	34	0	127.836	2211.94
34	40	56	63	20	122.608	5399.73
35	40	56	83	69	116.617	9888.65
36	40	56	59	50	120.369	7091.21
37	40	56	125	35	116.144	10409.1
38	40	56	113	59	115.057	11189.8
39	40	56	66	45	120.064	7221.32
40	40	63	31	0	128.227	2016.76
41	40	56	176	161	107.627	21924.2
42	40	64	17	0	130.265	1105.97
43	40	56	140	85	111.844	14637.8
44	40	56	78	0	123.059	5074.44
45	40	56	175	177	107.304	22900
46	40	56	76	71	117.091	9563.37
47	40	56	113	67	114.49	11710.2
48	40	56	138	64	113.266	13141.5
49	40	42	2	12	130.838	910.797
50	40	56	151	86	111.326	15418.5

The most frequent locations are buses number 40 and 56. The trade-off is picked on row 37 of table equivalent to 125 and 35 MW respectively. There is 11% loss reduction down to 117.5 MW .The result is demonstrated in Figure 5.18.

Branch Data

Brnch #	From Bus	To Bus	From Bus Injection P (MW)	From Bus Injection Q (MVAr)	To Bus Injection P (MW)	To Bus Injection Q (MVAr)	Loss (I^2 * Z) P (MW)	Loss (I^2 * Z) Q (MVAr)
1	1	2	-12.42	-13.02	12.51	10.99	0.098	0.32
2	1	3	-38.58	-17.08	38.83	16.90	0.249	0.82
3	4	5	-102.87	-26.79	103.07	27.49	0.200	0.90
4	3	5	-67.96	-14.53	69.20	17.30	1.234	5.53
5	5	6	88.19	4.14	-87.26	-1.36	0.925	4.20
6	6	7	35.26	-4.71	-35.20	4.44	0.059	0.27
7	8	9	-440.64	-89.73	445.25	24.43	4.620	57.75
8	8	5	337.27	124.65	-337.27	-92.14	0.000	32.51
9	9	10	-445.25	-24.43	450.00	-51.04	4.745	59.22
10	4	11	63.87	-0.14	-63.01	1.24	0.856	2.82
11	5	11	76.82	3.04	-75.62	-0.74	1.196	4.02
12	11	12	34.19	-35.07	-34.04	35.06	0.146	0.48
13	2	12	-32.51	-19.99	32.80	19.41	0.283	0.93
14	3	12	-9.87	-12.37	9.98	8.83	0.107	0.35
15	7	12	16.20	-6.44	-16.18	5.69	0.026	0.10
16	11	13	34.45	11.57	-34.14	-12.35	0.308	1.01
17	12	14	17.55	2.84	-17.48	-4.37	0.071	0.23
18	13	15	0.14	-3.65	-0.14	-2.24	0.000	0.00
19	14	15	3.48	3.37	-3.45	-8.07	0.028	0.09
20	12	16	7.74	4.11	-7.72	-6.12	0.019	0.07
21	15	17	-97.95	-27.09	99.39	27.55	1.434	4.75
22	16	17	-17.28	-3.88	17.42	-0.13	0.141	0.56
23	17	18	77.50	26.00	-76.67	-23.83	0.834	3.42
24	18	19	16.67	17.43	-16.59	-18.18	0.071	0.31
25	19	20	-6.30	3.58	6.32	-6.24	0.017	0.08
26	15	19	11.42	15.75	-11.37	-16.53	0.050	0.16
27	20	21	-24.32	3.24	24.44	-4.66	0.122	0.56
28	21	22	-38.44	-3.34	38.77	2.61	0.337	1.56
29	22	23	-48.77	-7.61	49.65	7.77	0.876	4.07
30	23	24	30.31	5.20	-30.18	-9.66	0.132	0.48
31	23	25	-172.41	-22.55	177.10	37.52	4.691	24.06
32	26	25	99.57	21.89	-99.57	-18.34	0.000	3.55
33	25	27	142.47	30.03	-136.16	-15.67	6.310	32.35
34	27	28	31.60	-0.35	-31.39	-0.75	0.204	0.91
35	28	29	14.39	-6.25	-14.33	4.28	0.060	0.24
36	30	17	230.15	95.65	-230.15	-72.83	0.000	22.82
37	8	30	75.37	25.48	-75.02	-72.88	0.351	4.10
38	26	30	214.43	-13.86	-210.78	-37.81	3.650	39.29
39	17	31	18.86	10.59	-18.61	-13.62	0.246	0.81
40	29	31	-9.67	-8.28	9.68	7.57	0.018	0.06
41	23	32	85.45	6.58	-83.08	-9.28	2.365	8.60
42	31	32	-27.07	11.45	27.35	-12.85	0.284	0.94
43	27	32	12.73	1.71	-12.69	-3.36	0.041	0.14
44	15	33	0.12	-2.20	-0.12	-0.81	0.000	0.00
45	19	34	-10.74	-8.11	10.85	2.51	0.116	0.38
46	35	36	2.33	3.51	-2.33	-3.77	0.000	0.00
47	35	37	-35.33	-12.51	35.49	11.95	0.159	0.72
48	33	37	-22.88	-8.19	23.13	5.52	0.249	0.85
49	34	36	28.75	5.17	-28.67	-5.48	0.077	0.24
50	34	37	-108.05	-39.24	108.40	39.56	0.348	1.28
51	38	37	185.05	120.49	-185.05	-103.32	0.000	17.17
52	37	39	13.81	13.19	-13.68	-15.35	0.131	0.43

53	37	40	4.22	8.57	-4.15	-12.38	0.079	0.22
54	30	38	55.64	15.04	-55.44	-52.80	0.208	2.42
55	39	40	-13.32	4.35	13.36	-5.68	0.040	0.13
56	40	41	38.46	-5.33	-38.23	4.96	0.231	0.78
57	40	42	11.33	-13.37	-11.18	9.41	0.149	0.49
58	41	42	1.23	-14.96	-1.15	11.95	0.079	0.26
59	43	44	-8.59	-3.89	8.64	-1.77	0.048	0.19
60	34	43	9.45	-0.80	-9.41	-3.11	0.039	0.16
61	44	45	-24.64	3.49	24.78	-5.09	0.145	0.58
62	45	46	-31.10	-4.37	31.50	2.43	0.400	1.35
63	46	47	-25.22	-4.10	25.46	1.68	0.242	0.81
64	46	48	-15.28	-5.64	15.43	1.25	0.145	0.46
65	47	49	-23.96	-4.47	24.07	3.15	0.108	0.35
66	42	49	-41.84	-4.30	43.13	1.44	1.290	5.83
67	42	49	-41.84	-4.30	43.13	1.44	1.290	5.83
68	45	49	-46.68	-2.78	48.21	2.44	1.528	4.15
69	48	49	-35.43	3.37	35.65	-4.07	0.218	0.62
70	49	50	50.67	14.12	-49.96	-14.04	0.710	2.00
71	49	51	63.14	21.14	-61.05	-18.65	2.088	5.88
72	51	52	27.66	6.52	-27.49	-7.30	0.177	0.51
73	52	53	9.49	2.30	-9.44	-5.78	0.047	0.19
74	53	54	-13.56	-5.22	13.62	2.69	0.058	0.27
75	49	54	34.89	13.51	-33.83	-16.58	1.056	4.18
76	49	54	34.94	11.75	-33.73	-14.86	1.211	4.05
77	54	55	6.88	1.50	-6.87	-3.30	0.010	0.04
78	54	56	6.52	7.79	-6.52	-8.44	0.003	0.01
79	55	56	-27.95	-3.69	27.99	3.48	0.043	0.13
80	56	57	-20.19	-10.35	20.38	8.63	0.186	0.52
81	50	57	32.96	10.04	-32.38	-11.63	0.578	1.64
82	56	58	-4.30	-4.75	4.31	2.57	0.012	0.03
83	51	58	16.39	4.14	-16.31	-5.57	0.080	0.23
84	54	59	-24.46	-9.21	24.81	5.19	0.353	1.61
85	56	59	-22.44	-6.40	22.91	2.48	0.470	1.43
86	56	59	-23.54	-6.27	24.04	2.73	0.502	1.49
87	55	59	-28.19	-10.12	28.63	6.85	0.445	2.03
88	59	60	-39.11	2.36	39.62	-3.72	0.505	2.31
89	59	61	-47.33	3.71	48.10	-4.00	0.768	3.51
90	60	61	-108.30	7.92	108.62	-7.74	0.316	1.62
91	60	62	-9.31	-7.19	9.33	5.81	0.016	0.07
92	61	62	24.98	-13.75	-24.91	13.08	0.067	0.30
93	63	59	135.95	68.50	-135.95	-59.73	0.000	8.77
94	63	64	-135.95	-68.50	136.35	52.55	0.401	4.66
95	64	61	21.70	15.83	-21.70	-15.64	0.000	0.19
96	38	65	-129.62	-67.68	131.28	-15.67	1.661	18.17
97	64	65	-158.05	-68.38	158.82	39.35	0.763	8.57
98	49	66	-117.37	-0.28	119.73	9.66	2.360	12.05
99	49	66	-117.37	-0.28	119.73	9.66	2.360	12.05
100	62	66	-37.14	-17.27	37.91	14.68	0.768	3.47
101	62	67	-24.28	-14.42	24.47	12.15	0.196	0.89
102	65	66	-22.50	72.32	22.50	-70.48	0.000	1.84
103	66	67	53.13	19.28	-52.47	-19.15	0.661	3.00
104	65	68	123.40	-29.40	-123.19	-32.50	0.208	2.41
105	47	69	-35.50	2.80	36.56	-6.78	1.060	3.49
106	49	69	-26.07	1.60	26.74	-8.18	0.670	2.20
107	68	69	-34.81	109.74	34.81	-105.48	0.000	4.26
108	69	70	92.84	17.84	-90.26	-19.36	2.580	10.92
109	24	70	5.10	-3.06	-5.10	-6.77	0.001	0.12
110	70	71	6.02	-9.88	-6.01	9.07	0.011	0.05

111	24	72	12.08	0.79	-12.01	-5.23	0.077	0.31
112	71	72	0.00	1.61	0.01	-5.88	0.007	0.03
113	71	73	6.01	-10.67	-6.00	9.59	0.012	0.06
114	70	74	19.45	11.98	-19.22	-14.38	0.233	0.77
115	70	75	3.88	8.50	-3.83	-11.75	0.053	0.17
116	69	75	99.71	22.37	-95.63	-22.53	4.077	12.28
117	74	75	-48.78	-7.95	49.11	8.07	0.326	1.08
118	76	77	-62.12	-20.65	64.23	24.18	2.107	7.02
119	69	77	46.49	10.77	-45.79	-19.29	0.700	2.29
120	75	77	-35.89	-8.93	36.74	6.92	0.855	2.84
121	77	78	41.56	7.60	-41.50	-8.66	0.067	0.22
122	78	79	-29.50	-17.34	29.57	16.97	0.063	0.28
123	77	80	-104.52	-34.26	106.52	35.04	2.006	5.72
124	77	80	-48.20	-19.30	48.97	19.67	0.771	2.75
125	79	80	-68.57	-28.60	69.40	30.41	0.837	3.78
126	68	81	-26.13	-5.93	26.16	-74.46	0.033	0.38
127	81	80	-26.16	74.46	26.16	-72.43	0.000	2.03
128	77	82	-5.03	18.25	5.18	-25.94	0.155	0.44
129	82	83	-47.58	24.57	47.92	-27.15	0.339	1.11
130	83	84	-24.93	14.77	25.49	-16.06	0.566	1.20
131	83	85	-42.99	12.07	43.89	-12.34	0.904	3.11
132	84	85	-36.49	9.06	36.94	-9.30	0.448	0.95
133	85	86	17.17	-7.35	-17.05	5.09	0.119	0.42
134	86	87	-3.95	-15.09	4.00	11.02	0.053	0.39
135	85	88	-50.58	7.66	51.12	-7.57	0.544	2.77
136	85	89	-71.43	0.73	72.69	3.73	1.259	9.11
137	88	89	-99.12	-2.43	100.52	7.69	1.401	7.18
138	89	90	58.20	-4.72	-56.46	5.81	1.739	6.31
139	89	90	110.80	-5.44	-107.91	7.06	2.893	12.12
140	90	91	1.37	4.44	-1.36	-6.48	0.008	0.03
141	89	92	201.28	-2.08	-197.31	16.88	3.971	20.26
142	89	92	63.51	-5.05	-61.94	7.26	1.573	6.33
143	91	92	-8.64	-6.61	8.68	3.57	0.040	0.13
144	92	93	57.56	-11.66	-56.65	12.49	0.902	2.96
145	92	94	52.10	-15.21	-50.68	15.89	1.418	4.66
146	93	94	44.65	-19.49	-44.12	19.42	0.537	1.76
147	94	95	40.99	8.96	-40.75	-9.25	0.238	0.78
148	80	96	19.67	20.93	-19.36	-24.44	0.311	1.59
149	82	96	-11.61	-6.08	11.63	0.82	0.024	0.08
150	94	96	19.93	-9.88	-19.80	8.04	0.130	0.42
151	80	97	27.13	25.62	-26.88	-27.03	0.248	1.26
152	80	98	29.27	8.26	-29.06	-10.35	0.210	0.95
153	80	99	19.88	8.11	-19.66	-12.86	0.217	0.99
154	92	100	31.38	-16.52	-30.59	15.33	0.784	3.57
155	94	100	3.88	-50.39	-3.47	45.65	0.411	1.34
156	95	96	-1.25	-21.75	1.33	20.56	0.079	0.25
157	96	97	-11.80	-19.99	11.88	18.03	0.087	0.44
158	98	100	-4.94	2.35	4.96	-7.23	0.018	0.08
159	99	100	-22.34	-4.67	22.43	2.86	0.090	0.41
160	100	101	-16.63	22.86	16.86	-25.10	0.236	1.07
161	92	102	44.53	-8.38	-44.27	8.11	0.256	1.16
162	101	102	-38.86	10.10	39.27	-11.11	0.411	1.87
163	100	103	121.75	-22.15	-119.40	24.36	2.351	7.72
164	100	104	56.18	10.65	-54.73	-9.41	1.455	6.58
165	103	104	32.45	13.87	-31.85	-15.83	0.597	2.03

166	103	105	43.35	12.85	-42.25	-13.48	1.103	3.35
167	100	106	60.36	9.48	-58.14	-7.12	2.225	8.42
168	104	105	48.58	2.63	-48.33	-2.61	0.250	0.95
169	105	106	8.86	3.88	-8.85	-5.15	0.015	0.06
170	105	107	26.75	-2.37	-26.35	-0.55	0.407	1.41
171	105	108	23.97	-11.13	-23.77	9.92	0.191	0.51
172	106	107	23.98	-3.73	-23.65	0.55	0.331	1.14
173	108	109	21.77	-10.92	-21.71	10.39	0.066	0.18
174	103	110	60.60	8.35	-59.15	-6.15	1.450	6.73
175	109	110	13.71	-13.39	-13.61	11.77	0.102	0.28
176	110	111	-35.70	0.96	36.00	-1.84	0.297	1.02
177	110	112	69.46	-30.61	-68.00	28.51	1.459	3.78
178	17	113	5.99	5.83	-5.98	-6.56	0.007	0.02
179	32	113	0.15	-16.66	-0.02	12.15	0.135	0.44
180	32	114	9.26	1.80	-9.25	-3.25	0.013	0.06
181	27	115	20.83	5.04	-20.75	-6.50	0.082	0.37
182	114	115	1.25	0.25	-1.25	-0.50	0.000	0.00
183	68	116	184.13	-71.31	-184.00	56.30	0.128	1.52
184	12	117	20.15	5.20	-20.00	-8.00	0.153	0.65
185	75	118	39.24	24.14	-38.90	-24.14	0.333	1.10
186	76	118	-5.88	-10.28	5.90	9.14	0.024	0.08
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						Total:	116.144	690.32

Figure 5.18 Power flow of IEEE 118 bus system with two added DG on bus 40 and 56 equivalent to 125 and 35 respectively

5.8 Summary

In this chapter the proposed NSGA-II – MATPOWER was applied on IEEE bus systems. The optimisation engine is programmed to avoid singular Jacobian matrix for the convergence. The capacities and locations were considered as design variables and objective functions as total real power loss of system and cost of additional DGs. As swing bus compensates for the equality constraint to maintain the demand/generation flow, in some cases such as IEEE 14 and 30 bus system, it could demand a huge flow from substation that might lead to congestions on the line. For such cases, a cost penalty function was introduced as parabola curve to increase the cost hence the optimisation search for better location and sizes if possible. The proposed parabola is an exponential function. Besides convergence, the optimisation is fast taking advantage of deterministic Newton power flow calculations. It was demonstrated for all cases that significant improvement in loss was achieved with the discussion on the cost of DG and preference of DNO for choosing array of non-dominated solutions represented in a Pareto front.

Chapter 6

Conclusions and Further Work

6.1 Conclusions

This chapter firstly presents the conclusion of this thesis, which is divided into five groups: conclusion from the multi-objectiveness and DG integration issues, heuristic and non-heuristic optimisation, planning cost, design variables and Pareto-based optimisation. This chapter also summarises the contributions of this thesis and proposes further work for the improvement and development of the planning framework presented.

6.1.1 Conclusion from the Multi-Objectiveness and Integration Issues

The comprehensive review of different multi-objective methods in power system problems and DG integration is presented in Chapter 2 and the related detailed theories in Chapter 3 shows the numerical challenges of finding optimum location and size of DG resources. It is also imperative to present the challenges and differences in literature with regards to DG models which is presented in Sections 2.7 and 2.8. Analysis tools are significant to evaluate the models and goals in planning the DG location and size. Uncertainties in DG planning and order of evaluation is the other aspect of it which is discussed in Sections 2.9, 2.10 and 3.3. The integration issues and significance of multi-objectiveness in DG resources optimum allocation are summarised next:

- There are various objectives in the optimisation of potential DG integration which in most cases, are in contrast with each other, meaning that increasing one objective will decrease the second one. In addition in most cases, there is no linear co-relation between defined objectives which results in non-convexity of searching space.

Therefore it imposes numerical challenges in the efficient and applicable method.

- Traditionally, aggregation of objectives in the optimisation was the dominant solutions by using techniques such as weighting methods or sequential programming (master-slave) which didn't give the ability of individual analysis on each objective.

6.1.2 Conclusion from the Heretic and Non-Heuristic Optimisation

The optimisation techniques in addressing the optimum size and location issues or their application in power system to lower the cost and increase the reliability, is mainly divided into two main categories of heuristic and conventional (non-heuristic) algorithms presented in Section 3.2. Any power system is limited to its technical and environmental constraints. Section 3.4 presents the concepts on how power flow should be managed within equality and inequality constraints with respect to existing algorithms in Section 3.2.

6.1.3 Conclusion from the Planning Cost

Addition of DG to a power system network has the potential of decreasing the cost imposed to a system. For example the proper (optimum) placement of a DG leads to differing network feeders or substation upgrades which happens as a result of load growth. The balance of technical issues and the cost is always a big part of any network developer. In Section 3.5 the concept of cost over a period of time considering the inflation is described. The definition of cost discussed in this Section comprises the calculation of total capital and running cost of candidate DG to the network. The cost is used as an objective function in 2-dimensional optimisation space in case studies presented in Chapter 5. Section 5.2 incorporates this objective into the proposed optimisation engine.

6.1.4 Conclusion from the Design Variables

The variables in the proposed methods are represented in a discrete space in Chapter 4 as the locations of candidate DGs are not continuous. The variables which are of interest are named design variables. Design variables used in this work are capacities and location of DGs. Various optimisation objectives are optimised in Section 4.3.2. The variables and value of functions (objectives) are known in this Section to verify the competence of the method. The efficiency of the proposed platform is tested by applying the benchmark functions.

6.1.5 Conclusion from the Pareto-based Optimisation in NSGA-II

The results generated in Chapter 5 are represented in a Pareto based. Pareto based platform is used for the representation of results. The value of each parameter is also generated in all Sections of Chapter 5 which are in fact the optimum point values. The cost discussed in Section 7.5 is optimised against the total real values which are generated in both GUI Pareto and population .txt file. The study of Pareto-based results is used to check the magnitude of power flow in Section 5.4. In this Section a penalty cost function is proposed to restrain the power flow passing the substation.

6.2 Contribution to Knowledge

The proposed optimisation for power system platform provides a novel and efficient MATPOWER – based optimisation engine which is capable of addressing issues discussed in Section 2.2 and 2.3 in terms of finding the optimum point for location and capacities of DGs in a power system network. In this thesis DGs are modelled as absorbent / producer of reactive power or negative load models which unlike the literature, doesn't restrict the planner into any specific type of DG resources. The economic and technical aspect of the integration is both considered in order to minimise the total loss of system through analysis of obtained Pareto. The novelty of the thesis lies within the analysis of Pareto curve. For example for the case study in Section 5.7, the proportionate DG capacity is adjusted to obtain the acceptable outcome. Another novelty in this thesis is the frequency of obtained locations which specifies the preference one location over another. If the frequency of two defined locations does not outnumber other possible locations, the constraints should be eased off. Jacobian matrix is prevented from singularity so non-convergence does not occur in the optimisation process which is another feature of the contribution. As cited in Section 2.2, in DG integration, connection of two separate DG operated networks is not a viable solution is most cases, hence if the planner considers the minimisation of power flow from a specific busbar, i.e. slack bus; this could contribute to autonomy of distribution network. The proposed penalty function in Section 5.4 directs the optimisation to less dependency of network from imported power flow with respect to the pre-defined objectives and constraints. The analysis of Pareto-curve and number of location frequency is again useful for the analysis of applicability from the obtained results, suitable to planner point of view.

6.3 Further Work

The range of issues addressed within this thesis offer several opportunities to further the work presented by extension, or development of the proposed method.

6.3.1 Design and DG variables

The work presented in Chapter 4 and 5 adopts DGs as generation of real power to maintain the generality. As the developers might consider a certain type of DG development of design variables can be altered with respect to the DG type.

6.3.2 Planning Cost

Planning cost in this work is restricted to the DG. As reinforcing of a power network might not be solely addressed by DG addition, developing more complicated cost models could be adapted to consider costs such as feeder or transformer upgrade.

6.3.3 Correction/Penalty Objectives and Functions

Defining DG objectives is not limited to loss or cost. Environmental or other technical issues could be addressed; however as the main focus of the thesis is to present a novel approach, contradictory objectives such as cost and loss are adopted. Those present two of most popular realistic objective of any developer which could be developed or altered. Furthermore tighter restriction on any other variable or objective is achievable but the mathematical model should be designed for that respect.

6.3.4 Deterministic Power Flow

Based on the time planning, or whether the network planner is trying to respond to the peak time demand of a network, uncertainties in load variation is addressed by deterministic or probabilistic power flow. The heavy stochastic mathematical calculation in probabilistic load flow could be developed for the program.

References

[1] K. D. Mistry, R. Roy, "Enhancement of Loading Capacity of Distribution System through Distributed Generator Placement Considering Techno economic Benefits with Load Growth, in *International Journal of Electrical Power & Energy Systems*, Vol. 54, January 2014, pp. 505-515

[2] R.F. Hirsh, B. K. Sovacool, R.D. Badinelli, in Operation and Control of Electric Energy Processing Systems, in *Distributed Generation and Momentum Change in the American Electric Utility System,* New Jersey, Wiley, 2010, pp. 157-170.

[3] M. Lehtonen, S. Nye, "History of electricity network control and distributed generation in the UK and western Denmark", *in First International Conference on Infrastructure Systems and Services: Building Networks for a Brighter Future (INFRA)*, Nov. 2008, pp.1-6.

[4] G. Simmonds, "Regulation of the UK Electricity Industry", CRI Industry Brief. Centre for the Study of Regulated Industries, University of Bath, 2002

[5] L. Karim, A. Pollitt, M. Pollit, "Integrating Distributed Generation: Regulation and Trends in Three Leading Countries", Energy Policy Group, University of Cambridge, 2014

[6] N. Acharya, P. Mahat, N. Mithulananthan, " An analytical approach for DG allocation in primary distribution network", Int. J. Electr. Power Energy Syst., December 2006, pp. 669-678.

[7] G.P. Harrison and A. R. Wallace, "Maximizing distributed generation capacity in deregulated markets", in *Proc. IEEE/Power Eng.Soc. Transm. Distrib. Conf. Expo.*, Dallas, TX, Sep. 2003, pp. 527-530.

[8] A. Berizzi, M. Innorta, and P. Marannino, "Multiobjective optimization techniques applied to modern power systems". In *2001 IEEE Power Engineering Society Winter Meeting*, Columbus, OH, Jan 28-Feb 1 2001.

[9] C.L. Wadhwa, N.K. Jain, "Multiple objective optimal load flow a new perspective", *IEEE Proceedings-Generation, Transmission and Distribution*, Vol. 137, n. 1, Jan. 1990, pp 13-18.

[10] U. Nangia, N. K. Jain, C. L. Wadhwa, "Optimal weight assessment based on a range of objectives in a multi-objective optimal load flow

study", *IEEE Proceedings - Generation, Transmission and Distribution,* Vol. 145, no. 1, Jan. 1998, pp. 65-69.

[11] G. Celli, F. Pilo, "Optimal distributed generation allocation in MV distribution networks", *Power Industry Computer Applications. PICA. 22nd IEEE Power Engineering Society International Conference.* 2001, pp. 81-86.

[12] M.J. Jahromi, E. Farjah, M. Zolghadri, "Mitigating voltage sag by optimal allocation of Distributed Generation using Genetic Algorithm", *Electrical Power Quality and Utilisation, EPQU 2007. 9th International Conference,* Oct. 2007, pp.1-6.

[13] F.S. Abu-Mouti, M.E El-Hawary, "Optimal Distributed Generation Allocation and Sizing in Distribution Systems via Artificial Bee Colony Algorithm", *IEEE Transactions on Power Delivery,* vol.26, no.4, Oct. 2011, pp. 2090-2101.

[14] A. Keane, L.F. Ochoa, C.L.T Borges, G.W Ault, A.D. Alarcon-Rodriguez, R.A.F Currie, F. Pilo, C. Dent, G.P. Harrison, "State-of-the-Art Techniques and Challenges Ahead for Distributed Generation Planning and Optimization" *IEEE Transactions on Power Systems,* vol.28, no.2, May 2013, pp.1493-1502.

[15] R.A. Jabr, B.C. Pal, "Ordinal optimisation approach for locating and sizing of distributed generation" *IET Generation, Transmission & Distribution,* vol.3, no.8, August 2009, pp. 713-723.

[16] M.R. Irving, Y.H. Song, "Optimisation Techniques for Electrical Power Systems - Part 1 Mathematical Optimisation Methods", Power Engineering Journal, Vol. 14, No. 5, October 2000.

[17] J.A. Momoh, Linear programming and application in *Electric power system applications of optimization,* New York: Mercel Dekker, 2001, pp. 143.

[18] Z. Wenjuan, L. Fangxing, L.M Tolbert, "Review of Reactive Power Planning: Objectives, Constraints, and Algorithms", *IEEE Transactions on Power Systems*, vol.22, no.4, Nov. 2007, pp.2177-2186.

[19] E.G. Birgin, N. Krejíc, J.M. Martínez, "Solution of bounded nonlinear systems of equations using homotopies with inexact restoration" Int. J. Comput. Math. , 2003, pp. 211-222.

[20] I.E. Grossmann, "Mixed-integer nonlinear programming techniques for process systems engineering", *Lecture notes*, Department of chemical engineering, Carnegie Mellon University, Jan. 1999.

[21] J. F. Benders, “Partitioning methods for solving mixed variables programming problems”, *Numerische Mathematik*, vol. 4, 1962, pp. 238-252.

[22] T. Gomez, I. J. Perez-Arriaga, J. Lumbreras, V. M. Parra, “A security-constrained decomposition approach to optimal reactive power planning”, *IEEE Trans. Power Syst.,* vol. 6, no. 3, Aug. 1991, pp. 1069-1076.

[23] S. Granville, M. V. P. Pereira, A. Monticelli, “An integrated methodology for VAR sources planning”, *IEEE Trans. Power Syst*., vol. 3, no. 2, May 1988, pp. 549–557.

[24] M. Gilli, P. Winker, "Review of Heuristic Optimization Methods in Econometrics", Working Papers 001, COMISEF, 2008.

[25] R. Baños, F. Manzano-Agugliaro, F.G. Montoya, C. Gil, A. Alcayde, J. Gómez,” Optimization methods applied to renewable and sustainable energy: A review”, Renewable and Sustainable Energy Reviews, vol. 15, Iss. 4, May 2011, pp. 1753-1766.

[26] S. Kirkpatrick, C. D. Gelatt Jr., M. P. Vecchi, ”Optimization by Simulated Annealing”**,** Science 13, May 1983.

[27] A. Colorni, M. Dorigo, V. Manniezzo, ” Distributed optimization by ant colonies”, In *Proceedings of the First European Conference on Artificial Life (ECAL-91)* The MIT Press. Cambridge MA, 1992, pp. 134–142.

[28] A. Colorni, M. Dorigo, V. Manniezzo, “ An investigation of some properties of an ant algorithm. In *Parallel problem solving from nature,* Vol 2, North-Holland, Amsterdam, 1992, pp. 509–520.

[29] E. Carpaneto and G. Chicco, “Ant-colony search-based minimum losses reconfiguration of distribution systems,” In *Proc of the 12th IEEE Mediterranean Electrotechnical Conference*, Vol. 3, May 2004, pp. 971-974.

[30] R. Annaluru, S. Das and A. Pahwa, “Multi-level ant colony algorithm for optimal placement of capacitors in distribution systems”, In *Congress on Evolutionary Computation*, Vol. 2, June 2004, pp. 1932-1937.

[31] S-J. Huang, “Enhancement of hydroelectric generation scheduling using ant colony system based optimization approaches”, *IEEE Trans. on Energy Conversion*, Vol. 16, Iss. 3, Sept. 2001, pp. 296-301.

[32] I.K. Yu and Y.H. Song, “A novel short-term generation scheduling technique of thermal units using ant colony search algorithms”, Electric Power and Energy Systems, Vol. 23, 2001, pp. 471-479.

[33] Y.H. Song, C.S. Chou and T.J. Stonham, “Combined heat and power economic dispatch by improved ant colony search algorithm”, Electric Power Systems Research, Vol. 52, 1999, pp. 115-121.

[34] J.H. Teng , Y.H. Liu, “A novel ACS-based optimum switch relocation method”, *IEEE Trans. on Power Systems*, Vol. 18, No. 1 Feb. 2003, pp. 113-120.

[35] Y.J. Jeon, J.C. Kim, S.Y. Yun, K.Y. Lee, “Application of ant colony algorithm for network reconfiguration in distribution systems”, In *Proc. IFAC Symposium for Power Plants and Power Systems Control*, Seoul, Korea, June 2003, pp. 266-271.

[36] M.G. Ippolito, E.R. Sanseverino , F. Vuinovich, “Multiobjective ant colony search algorithm optimal electrical distribution system planning”, In *Congress on Evolutionary Computation*, Vol. 2, June 2004, pp. 1924-1931.

[37] J.G. Vlachogiannis, N.D. Hatziargyriou , K.Y. Lee, “Ant colony system based algorithm for constrained load flow problem”, *IEEE Trans. on Power Systems,* Vol. 20, No. 3, Aug. 2005, pp. 1241-1249.

[38] K.Y. Lee and J.G. Vlachogiannis, “Ant colony optimization for active/reactive operational planning,” In *16th World IFAC Conf*., July 2005.

[39] Y.H. Song and C.S. Chou, “Application of ant colony search algorithms in power system optimisation”, IEEE Power Engineering Review, Vol. 18, No. 12, 1998, pp. 63-64.

[40] K.Y. Lee, J.G. Vlachogiannis, "Optimization of Power Systems based on Ant Colony System Algorithms: An Overview", *Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems*, Nov. 2005, pp. 22-35.

[41] R.C. Eberhart, J. Kennedy,”A new optimizer using particle swarm theory” In *Proceedings of the Sixth International Symposium on Micromachine and Human Science*, 1995, pp. 39-43.

[42] M. Eslami, H. Shareef ,A. Mohamed ,S.P. Ghoshal ," Tuning of power system stabilizers using particle swarm optimization with passive congregation", Int. J. Phys. Sci., No. 5, 2010 ,pp. 2574- 2589.

[43] W. Kuersuk , W. Ongsakul, "Optimal placement of Distributed Generation using particle swarm optimization", *Australian Universities Power Engineering Conference 2006 (AUPEC 06)* , Dec. 2006.

[44] K. Zou, A.P. Agalgaonkar, K.M. Muttaqi, S. Perera, "Distribution System Planning With Incorporating DG Reactive Capability and System Uncertainties", *IEEE Transactions on Sustainable Energy*, vol.3, no.1, Jan. 2012, pp.112-123.

[45] A. Silversti, S. Buonaao, "Distributed generation planning using genetic algorithm", in *Proc. IEEE Int. Conf Electric Power Engineering,* August 2002, pp. 257.

[46] C.R. Reeves, J.E. Rowe, Introduction in *Genetic Algorithms – Principles and Perspectives*. Boston: Kluwer, 2003, pp.10-16.

[47] Y. Del Valle, G.K. Venayagamoorthy, S. Mohagheghi, J.C. Hernandez, R.G. Harley," Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power Systems," *IEEE Transactions on Evolutionary Computation*, vol.12, no.2, April 2008, pp. 171-195.

[48] K. Iba, "Reactive power optimization by genetic algorithm", *IEEE trans. on power systems*, Vol. 9 No. 2, 1994, pp 685-692.

[49] J.O. Kim, S.K. Park, K.W Park, C Singh, "Dispersed generation planning using improved Hereford Ranch algorithm", *Evolutionary Computation Proceedings*, *IEEE World Congress on Computational Intelligence,* May 1998, pp. 678-683.

[50] D.H. Popović, J.A. Greatbanks, M. Begović, A. Pregelj," Placement of distributed generators and reclosers for distribution network security and reliability", *International Journal of Electrical Power & Energy Systems*, vol. 27, Iss.s 5-6, June-July 2005, pp. 398-408.

[51] Gareth P. Harrison, Antonio Piccolo, Pierluigi Siano, et al. "Distributed Generation Capacity Evaluation Using Combined Genetic Algorithm and OPF", *International Journal of Emerging Electric Power Systems*, vol. 8, no. 2, 2007.

[52] W. El-Khattam, K. Bhattacharya, Y. G. Hegazy, M.M. A. Salama, "Optimal investment planning for distributed generation in a

competitive electricity market," *IEEE Trans. Power Syst.*, vol. 19, no. 3, Aug. 2004, pp. 1674-1684.

[53] G. Celli, E. Ghiani, S. Mocci, F. Pilo, "A multiobjective evolutionary algorithm for the sizing and siting of distributed generation", *IEEE Transactions on Power Systems*, vol.20, no.2, May 2005, pp. 750-757.

[54] G. Carpinelli, G. Celli, S. Mocci, F. Pilo, A. Russo, "Optimisation of embedded generation sizing and siting by using a double trade-off method", In *Proc IEEE, Generation, Transmission and Distribution* vol.152, no.4, July 2005, pp. 503-513,

[55] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol.6, no.2, Apr. 2002, pp.182-197.

[56] W. El-Khattam, M.M.A Salama, "Distributed generation technologies, definitions and benefits, Electric Power Systems Research, vol. 71, Iss. 2, Oct. 2004, Pages 119-128.

[57] T. Ackermann, G. Andersson, L. Söder, "Distributed generation: a definition", Electric Power Systems Research, vol. 57, Iss. 3, Apr. 2001.

[58] A. Baghipour, S. Fallahian, "A Study on Impact of DG and Load Models on Optimal Sizing and Sitting of DGs in Distribution Systems Using Genetic Algorithm", *On Applied mathematics in Engineering, Management and Technology* ,vol. 1 ,no. 4, 2013,pp. 387-398

[59] M. Begovic, A. Pregelj, A. Rohatgi, D. Novosel, "Impact of renewable distributed generation on power systems", *Proceedings of the 34th Annual International Conference on System Sciences,* , Jan. 2001, pp. 654-663.

[60] M. H. J. Bollen, H. Fainan, "Voltage margin and hostage capacity" in *Integration of Distributed generation in the power system,* Wiley-IEEE Press*,* 2011*,* pp. 149.

[61] A. Borbely and J.F. Kreider," Distributed Generation: A New Paradigm for the New Millenium", CRC Press, 2001.

[62] N. Jenkins, R. Allan, P. Crossley, D. Kirschen, G. Strbac, Embedded Generation, The Institution of Electrical Engineers, London, 2000.

[63] T. Gönen, in Electric Power Distribution System, McGraw-Hill Book Company, 1986.

[64] "Voltage Stability Assessment Concepts, Practices and Tools", IEEE PES Power System Stability Subcommittee, Tech. Rep., August 2002.

[65] M.H.J. Bollen,and H. Fainan ,transmission system operation in *Integration of Distributed generation in the power system,* Wiley-IEEE, 2011, p. 406.

[66] M. Abdel-Akher, A. A. Ali, A. M. Eid, H. El-Kishky, "Optimal size and location of distributed generation unit for voltage stability enhancement," *Energy Conversion Congress and Exposition (ECCE), 2011 IEEE* ,Sept. 2011 ,pp.104-108.

[67] S. A. Gareh, "Voltage stability assessment for distributed generation in islanded microgrid system", Master Thesis, July 2012, p. 4.

[68] M. Biglari, "Dynamics of voltage stability in multimachine system", *IEEE PES Power Systems Conference and Exposition proceedings*, Oct. 2004, pp. 366-371.

[69] M. Chakravorty, D. Das, "Voltage stability analysis of radial distribution networks," *Int. J. Elect. Power Energy Syst*., vol. 23, Feb. 2001, pp. 129-135.

[70] M. Ettehadi, H. Ghasemi, S. Vaez-Zadeh, "Voltage Stability-Based DG Placement in Distribution Networks", *IEEE Transactions on Power Delivery,* vol.28, no.1, Jan. 2013, pp.171-178.

[71] H.A. Gil, M. El Chehaly, G. Joos, C. Canizares, "Bus-based indices for assessing the contribution of DG to the voltage security margin of the transmission grid", *Power & Energy Society General Meeting, IEEE PES*, July 2009, pp.1-7.

[72] B. Gao, G.K. Morison, P. Kundur, "Voltage stability evaluation using modal analysis", *IEEE Transactions on Power Systems,* vol.7, no.4, Nov 1992, pp.1529-1542.

[73] V. Ajjarapu, Sensitivity analysis for voltage stability in *computational techniques for voltage stability assessment and control*, New York:Springer, 2006, p. 122.

[74] D. Westwick, Power plant and power system control,Oxford: Elsevier, 2006, pp.378.

[75] M.M. Aly, M. Abdel-Akher, "A continuation power-flow for distribution systems voltage stability analysis", *IEEE International Conference on Power and Energy, 2012*, pp.470-475.

[76] H. Hedayati, S.A. Nabaviniaki, A. Akbarimajd, "A Method for Placement of DG Units in Distribution Networks", *IEEE Transactions on Power Delivery*, vol.23, no.3, July 2008 ,pp.1620-1628.

[77] C. A. Cañizares, “Applications of optimization to voltage collapse analysis,” in *Proc. IEEE Power Eng. Soc. Summer Meeting*, San Diego, CA, USA, July 1998.

[78] H. L. Willis, Planning and the T&D planning process in Power Distribution Planning Reference Book. New York: Marcel Dekker, 2004, p. 988

[79] J.W.Taylor, P.E. McSharry, "Short-Term Load Forecasting Methods: An Evaluation Based on European Data", *IEEE Transactions on Power Systems*, vol.22, no.4, Nov. 2007, pp.2213-2219.

[80] H. L. Willis, Planning and the T&D planning process in Power Distribution Planning Reference Book. New York: Marcel Dekker, 2004, p. 992

[81] H. Yassami , A. Moeini, S.M.R Rafiei ,A. Darabi, A. Bagheri, “Optimal distributed generation planning considering reliability, cost of energy and power loss”, Scientific Research and Essays,vol. 6, 2011 pp.1963-1976

[82] L. G. B. Marzano, M. E. P Maceira, T. C. Justino, A.C.G Melo, M. L. V. Lisboa, "Integrating short and long-term energy expansion planning tools for more resilient mid-term energy plans for the Brazilian interconnected system," *Bulk Power System Dynamics and Control iREP Symposium,* Aug. 2010, pp.1-10

[83] S.M. Ryan, J.D. McCalley, D.L. Woodruff, “Long term resource planning for electric power systems under uncertainty”, Technical Report, Mar. 2010.

[84] John P. Stremel, "Generation System Planning Under Load Forecast Uncertainty", *IEEE Transactions on Power Apparatus and Systems*, vol. 100, no.1, Jan. 1981, pp. 384-393.

[85] B. Mo, J. Hegge, I. Wangensteen, "Stochastic generation expansion planning by means of stochastic dynamic programming", *IEEE Transactions on Power Systems,* vol.6, no.2, May 1991, pp.662-668.

[86] P. Siano, G.P. Harrison, P. Antonio, A.R Wallace,” Strategic placement of distributed generation capacity”, In *Proceedings of 19th international conference on electricity distribution*, 2007. pp. 1-4.

[87] G. P. Harrison, A. R. Wallace, "OPF evaluation of distribution network capacity for the connection of distributed generation", *Proceedings Inst. Elect. Eng. Gen. Transm. Dist.*, vol. 152, 2005, 115-122.

[88] K. Nara, Y. Hayashi, K. Ikeda, T. Ashizawa, "Application of tabu search to optimal placement of distributed generators", *Proceedings IEEE PES Winter Meeting*, vol. 1, 2001, pp. 918-923

[89] P. N. Vovos, G. P. Harrison, A. R. Wallace, J. W. Bialek, "Optimal Power Flow as a tool for fault level constrained network capacity analysis", *IEEE Transactions on Power Systems,* vol. 20, 2005, 734-741.

[90] A. Keane, M. O'Malley, 2005, "Optimal Allocation of Embedded Generation on Distribution Networks", *IEEE Transactions on Power Systems*, vol. 20, pp. 164 -166.

[91] P. N. Vovos and J. W. Bialek, "Direct incorporation of fault level constraints in optimal power flow as a tool for network capacity analysis", *IEEE Transactions on Power Systems*, vol.20. no.4, 2005, pp. 2125-2134

[92] K. H. Kim, Y. J. Lee, S. B. Rhee, S. K. Lee, S. K. You, "Dispersed generator placement using fuzzy-GA in distribution systems", *Proceedings IEEE PES Summer Meeting*, vol. 1, 2002, pp. 1148-1153

[93] B. Kuri, M. Redfern, F. Li, "Optimization of rating and positioning of dispersed generation with minimum network disruption" *Proceedings IEEE Power Eng. Soc. Gen. Meeting*, vol.1, 2004, pp.2074-2078

[94] W. El-Khaltam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama, "Optimal investment planning for distributed generation in a competitive electricity market", *IEEE Transactions on Power Systems,* vol.19, 2004, pp. 1674-1684

[95] M. Mardaneh, G.B Gharehpetian, "Siting and sizing of DG units using GA and OPF based technique", *TENCON 2004. IEEE Region 10 Conference*, vol. 3, Nov. 2004, pp.331-334.

[96] I.A. Farhat, M.E. El-Hawary," Optimization methods applied for solving the short-term hydrothermal coordination problem", *Electric Power Systems Research*, Vol. 79, Iss. 9, Sep. 2009, pp. 1308-1320

[97] M.T. Hagan, Behr, M. Suzanne , "The Time Series Approach to Short Term Load Forecasting", *IEEE Transactions on Power Systems,* vol.2, no.3, Aug. 1987, pp.785-791.

[98] A.D. Alarcon-Rodriguez," A Multi-objective Planning Framework for Analysing the Integration of Distributed Energy Resources". PhD

Thesis, Institute of Energy and Environment, University of Strathclyde, April 2009.

[99] J, D, Mc Calley, “Stochastic programming and its application to optimal generation planning”, *Lecture notes*, Department of electrical and computer engineering, Iowa State University, 2009

[100] S. N. Liew and G. Strbac, “Maximising penetration of wind generation in existing distribution networks,” *IEEE Proc. Gen., Transm. Distrib.*, vol. 149, no. 3, May 2002, pp. 256-262.

[101] H.M Khodr, J.F. Gomez, L. Barnique, J.H. Vivas, P. Paiva, "A linear programming methodology for the optimization of electric power-generation schemes", *IEEE Transactions on Power Systems*, vol.17, no.3, Aug 2002 ,pp.864-869.

[102] A. Keane, M. O'Malley, "Optimal Allocation of Embedded Generation on Distribution Networks", *IEEE Transactions on Power Systems*, vol.20, no.3, Aug. 2005, pp.1640-1646.

[103] A.A. Abou El-Ela, S.M. Allam, M.M. Shatla,” Maximal optimal benefits of distributed generation using genetic algorithms”, *Electric Power Systems Research*, Vol. 80, Iss. 7, July 2010, pp. 869-877.

[104] A.A. Abou EL Ela, A.Z. El-Din, S.R. Spea, "Optimal corrective actions for power systems using multiobjective genetic algorithms", *42nd International Universities Power Engineering Conference (UPEC)*, Sept. 2007, pp.365-376.

[105] J. Hazra, A. K. Sinha, “A multi-objective optimal power flow using particle swarm optimization”, *European Transactions on Electrical Power.* vol. 21, Iss. 1, Jan.2011, pp.1028-1045.

[106] Z. Yun, H. Zhang, Y. Liu, H Mu, M Lei, “Secondary voltage control based on multiple objective linear programming”, *Canadian Conference on Electrical and Computer Engineering*, May 2005 , pp.2212-2215.

[107] U. Nangia, N.K. Jain, C.L. Wadhwa, "Regret analysis of sequential goal programming for multi-objective optimal power flows", *The 7th International Power Engineering Conference (IPEC) vol.2, Dec.* 2005, pp.1200,1204.

[108] Arturo Alarcon-Rodriguez, Graham Ault, Stuart Galloway,” Multi-objective planning of distributed energy resources: A review of the state-of-the-art”, *Renewable and Sustainable Energy Reviews*, Vol. 14, Iss. 5, June 2010, pp. 1353-1366.

[109] N.S. Rau, W. Yih-Heui, "Optimum location of resources in distributed planning", *IEEE Transactions on Power Systems,* vol.9, no.4, Nov 1994 ,pp. 2014-2020.

[110] A. Ramos, I. J. Perez-Arriaga, J. Bogas, "A nonlinear programming approach to optimal static generation expansion planning", *IEEE Transactions on Power Systems,* vol.4, no.3, , Aug 1989, pp.1140,1146.

[111] J. Zhu, Optimisation of power system operation, in *Introduction*, 2nd ed, New Jeresy, Wiley, 2009, pp. 3-12.

[112] E.C. Finardi ,E.L Da Silva,C. Sagastizabal “Solving the unit commitment problem of hydropower plants via Lagrangian relaxation and sequential quadratic programming” *Computational and Applied Mathematics,* vol.24, no 3, 2005, pp.317-341.

[113] J. Lavaei, A. Rantzer, and S. H. Low, “Power flow optimization using positive quadratic programming,” *in Proc. 18th IFAC World Congr*., 2011.

[114] D.I. Sun, B. Ashley, B. Brewer, A. Hughes, W.F. Tinney, "Optimal power flow by Newton approach", IEEE Trans. on PAS, no. 10, Oct. 1984, pp. 2864-2880.

[115] T. Van Cutsem, "A method to compute reactive power margins with respect to voltage collapse", *IEEE Transactions on Power Systems,* vol.6, no.1, Feb. 1991, pp.145,156

[116] H. Singh, F. L. Alvarado:, “Weighted least absolute value state estimation using interior point method”, *IEEE Transactions on Power Systems*, vol. 9, , 1994 ,pp. 1478-1484

[117] V. H. Quintana, G. L. Torres, J. Medina-Palomo, “ Interior-Point Methods and their Applications to Power Systems: A Classification of Publications and Software Codes”, *IEEE Transactions on Power Systems*, vol. 15, no. 1, 2000 ,pp. 170-175.

[118] Y. C. Wu, A. S. Debs, R. E. Marsten, “A Direct Nonlinear Predictor-Corrector Primal-Dual Interior Point Algorithm for Optimal Power Flows”, *IEEE Transactions on Power Systems*, vol. 9, no. 2, 1994, pp. 876-883.

[119] R. A. Jabr, A. H. Cooninck, B. J. Cory, ”A Primal-Dual Interior Point Method for Optimal Power Flow Dispatching”, *IEEE Transactions on Power Systems*, vol. 17, no. 3, 2002 ,pp. 654-662.

[120] J. Momoh, S. Guo, E. Ogbuobiri, R. Adapa: “The quadratic interior point method for solving power systems optimization problems”, *IEEE Transactions on Power Systems*, vol. 9, 1994 ,pp. 1327-1336.

[121] J. Medina, V. H. Quintana, A. J. Conejo, F. P. Thoden, “A Comparison of Interior-Point Codes for Medium-Term Hydro-Thermal Coordination”, *IEEE PES Summer Meeting*, 1997.

[122] J. L. M. Ramos, A. T. Lora, J. R. Santos, A. G. Exposito, “Short-Term Hydro-Thermal Coordination Based on Interior Point Nonlinear Programming and Genetic Algorithms”, *IEEE Port PowerTech*, 2001.

[123] S. Grenville, J. C. O. Mello, A. C. G. Mello, “Application of interior point methods to power flow unsolvability”, *IEEE Transactions on Power Systems*, vol. 11, 1996, pp. 1096-1103.

[124] G. D. Irrisari, X. Wang, J. Tong, S. Mokhtari, “Maximum loadability of power systems using interior point nonlinear optimization methods”, *IEEE Transactions on Power Systems*, vol. 12, 1997 ,pp. 162-172.

[125] V. R. Sherkat, Y. Ikura, “Experience with Interior Point Optimization Software for a Fuel Planning Application”, *IEEE Transactions on Power Systems*, vol. 9, no. 2, 1994.

[126] Y. C. Huang, H.C. Sun, K.Y. Huang , “*Applications of Simulated Annealing-Based Approaches to Electric Power Systems ,* Department of Electrical Engineering, Cheng Shiu University, Kaohsiung, Taiwan.

[127] K.P. Wong, Y.W. Wong, "Short-term hydrothermal scheduling part. I. Simulated annealing approach", *Generation, Transmission and Distribution, IEEE Proceedings*, vol.141, no.5, Sep.1994, pp.497-501.

[128] M.R. Irving, M.J. H. Sterling ,”Optimal network tearing using simulated annealing‘. *In IEEE Proc.*, pp. 69-72.

[129] T. Satoh, K. Nara, ”Maintenance scheduling by using simulated annealing method”, *IEEE Transaction on Power Systems*, 1991, pp. 850-856.

[130] H.D. Chiang,J.C. Wang ,”Optimal capacitor placements in distribution systems. Part I : a new formulation and the overall problem”, *IEEE Transactions on Power Delivery,*1990, pp.634-640.

[131] C.W. Hasselfield, P. Wilson, L. Penner, M. Lau, A. M. Cole, “An automated method for least cost distribution planning”, *Power Industry Computer Application Conference, 1989* , pp. 83-89.

[132] K.P. Wong, C.C. Fung, “Simulated-annealing-based economic dispatch algorithm”, *Generation, Transmission and Distribution, IEEE Proceeding*, vol.140, no.6, Nov. 1993, pp. 509-515.

[133] R.F. Chu, J.C. Wang, H. D. Chiang, “ Strategic planning of LC compensators in non-sinusoidal distribution systems”, *IEEE Transactions on Power Delivery*, vol. 9, no. 3, July 1994, pp. 1558-1563.

[134] R. Billinton, S. Jonnavithula, “Optimal switching device placement in radial distribution systems” *IEEE Transactions on Power Delivery,* vol. 11, no. 3, July 1996, pp. 1646-1651.

[135] D. Jiang, R. Baldick, ” Optimal electric distribution system switch reconfiguration and capacitor control. IEEE Transactions on Power Systems, vol. 11, no. 2, May 1996, pp. 890-897.

[136] Y. J. Jeon, J.C. Kim, J.O. Kim, J. R. Shin, K.Y. Lee, “An efficient simulated annealing algorithm for network reconfiguration in large-scale distribution systems”, *IEEE Transactions on Power Delivery*, vol. 17, no. 4, October 2002, pp. 1070-1078.

[137] J.M. Nahman, D.M. Peric, ”Optimal planning of radial distribution networks by simulated annealing technique” *IEEE Transactions on Power Systems*, vol. 23, no. 2, May 2008, pp. 790-795.

[138] F. Glover,” Future Paths for Integer Programming and Links to Artificial Intelligence”, *Computers and Operations Research*, vol 13, 1986, pp. 533-549.

[139] N. Bakhta, H. Bouzeboudja, A. Allali, “Application of Tabu Search and Genetic Algorithm in Minimize Losses in Power System Using the B-Coefficient Method”, *Energy Proceeding*, vol. 36, 2013, pp. 687-693.

[140] M.A. Abido “Optimal power flow using tabu search algorithm”, *Electric Power Components & Systems*, vol.30, iss. 5, 2002, pp. 469-483

[141] A. Borghetti, A. Frangioni, F. Lacalandra, A. Lodi, “Lagrangian relaxation and Tabu Search approaches for the unit commitment problem” *Power Tech Proceedings, IEEE Porto* , vol.3, 2001, pp. 7

[142] H. Mori and T. Usami, “Unit commitment using tabu search with restricted neighborhood”, in *Proc. IEEE International Conference on Intelligent System Application to Power Systems*,1996 ,pp. 422-428.

[143] A.H. Mantawy, Y.L. Abdel-Magid and S.Z. Selim, “Unit commitment by tabu search”, *IEE Proc. Gener. Transm. Distrib*, vol. 145, Jan. 1998, pp. 56-64.

[144] A.Y. Abdelaziz, F.M. Mohamed, S.F. Mekhamer, M.A.L. Badr, ”Distribution system reconfiguration using a modified Tabu Search algorithm”, *Electric Power Systems Research*, vol. 80, iss. 8, August 2010, pp. 943-953.

[145] H. Mori, Y. Ogita, “A parallel tabu search method for reconfiguration of distribution systems”, *in: Proceedings IEEE Power Engineering Society Summer Meeting*, vol. 1, 2000, pp. 73-78.

[146] K.K. Li, T.S. Chung, G.J. Chen, G.Q. Tang,” A tabu search approach to distribution network reconfiguration for loss reduction”, *Electric Power Components and Systems* , 2004, pp. 571-585.

[147] G.K. Purushothama, L. Jenkins,”Simulated annealing with local search-a hybrid algorithm for unit commitment”, *IEEE Transactions on Power Systems*, vol. 18, no. 1, Feb. 2003, pp. 273-278.

[148] Y. J. Jeon, J. C. Kim,” Application of simulated annealing and tabu search for loss minimization in distribution systems”, Electric *Power and Energy Systems*, vol. 9, iss. 18, 2004.

[149] S.F. Mekhamer, A.Y. Abdelaziz, F.M. Mohammed, M.A.L. Badr, ”A new intelligent optimization technique for distribution systems reconfiguration”, in *Proceedings of the Twelfth International Middle-East Power Systems Conference* , March 2008, pp. 397-401.

[150] D. Zhang, Z. Fu, L. Zhang, “An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems”, *Electric Power Systems Research ,* 2007, pp. 685-694.

[151] J.M. Alvarado, E. V. Alvarado, M.A. Arevalo, "Ant Colony Systems Application for Electric Distribution Network Planning", *International Conference on Intelligent System Applications to Power Systems,* Nov. 2009, pp.1-6.

[152] J.F. Gomez, H.M Khodr, P.M De Oliveira, "Ant colony system algorithm for the planning of primary distribution circuits," *IEEE Transactions on Power Systems,* vol.19, no.2,May 2004 ,pp. 996-1004.

[153] M. Dorigo,V. Maniezzo, A. Colorni, "Ant system: optimization by a colony of cooperating agents", *IEEE Transactions on Systems,* vol.26, no.1, Feb. 1996, pp.29-41.

[154] M.G. Ippolito, G. Morana, E. Riva Sanseverino, F. Vuinovich, “Ant Colony Search Algorithm for Optimal Strategical Planning of Electrical Distribution Systems Expansion”, *Springer in Applied Intelligence* ,vol. 23, Iss. 3, 2005, pp. 139-152.

[155] M.R. AlRashidi, M.E El-Hawary, "A Survey of Particle Swarm Optimization Applications in Electric Power Systems," *IEEE Transactions on Evolutionary Computation,* vol.13, no.4, Aug. 2009 pp. 913-918.

[156] H. Xiaohui, S. Yuhui, R. Eberhart, “Recent advances in particle swarm,” *in Proc. Congr. Evol. Comput*., vol. 1, 2004, pp. 90-97

[157] R. C. Eberhart and Y. Shi, “Guest editorial”, *IEEE Trans. Evol. Comput*., vol. 8, no. 3, Jun 2004, pp. 201–203.

[158] H. Yoshida, Y. Fukuyama, S. Takayama, Y. Nakanishi, “A particle swarm optimization for reactive power and voltage control in electric power systems considering voltage security assessment”, in *Proc. IEEE Int. Conf. Syst.* vol. 6, 1999,pp. 497-502.

[159] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, Y. Nakanishi, “A particle swarm optimization for reactive power and voltage control considering voltage security assessment”, *IEEE Transactions on Power Systems,* vol. 15, no. 4, Nov 2000 ,pp. 1232-1239.

[160] Y. Fukuyama and H. Yoshida, “A particle swarm optimization for reactive power and voltage control in electric power systems,” *in Proc. Congr. Evol. Comput,* vol. 1, 2001,pp. 87–93.

[161] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi, “A particle swarm optimization for reactive power and voltage control considering voltage security assessment,” in *Proc. IEEE Power Eng. Soc. Winter Meeting*, vol. 2, *2001* ,pp. 498–504.

[162] J. B. Park, K. S. Lee, J. R. Shin, and K. Y. Lee, “A particle swarm optimization for economic dispatch with nonsmooth cost functions,” IEEE Trans. Power Syst., vol. 20, no. 1, pp. 34–42, Feb. 2005.

[163] A. I. El-Gallad, M. El-Hawary, A. A. Sallam, and A. Kalas, “Swarm intelligence for hybrid cost dispatch problem,” in *Proc. Canadian Conf. Elect. Comput. Eng*, vol. 2, 2001 ,pp. 753-757.

[164] A. El-Gallad, M. El-Hawary, A. Sallam, and A. Kalas, “Particle swarm optimizer for constrained economic dispatch with prohibited operating zones,” in *Proc. Canadian Conf. Elect. Comput. Eng.,* vol. 1, 2002, pp. 78–81.

[165] W. Zhang and Y. Liu, “Reactive power optimization based on PSO in a practical power system,” in *Proc. IEEE Power Eng. Soc. General Meeting*, 2004, pp. 239-243.

[166] G. Coath, M. Al-Dabbagh, and S. K. Halgamuge, “Particle swarm optimization for reactive power and voltage control with grid-integrated wind farms,” in *Proc. IEEE Power Eng. Soc. General Meeting*, 2004, pp. 303-308.

[167] B. Zhao, C. X. Guo, and Y. J. Cao, “Improved particle swam optimization algorithm for OPF problems”, in *Proc. IEEE/PES Power Syst. Conf. Expo.*, 2004, pp. 233-238.

[168] M. A. Abido, “Optimal power flow using particle swarm optimization,” *Int. J. Elect. Power Energy Syst*., vol. 24, no. 7, 2002 ,pp. 563-571.

[169] S. He, J. Y. Wen, E. Prempain, Q. H. Wu, J. Fitch, and S. Mann, “An improved particle swarm optimization for optimal power flow,” in *Proc. Int. Conf. Power Syst. Technol*., vol. 2, 2004, pp. 1633-1637.

[170] C. Juang and C. Lu, “Power system load frequency control by evolutionary fuzzy PI controller”. in *Proc. IEEE Int. Conf. Fuzzy Syst*., vol. 2, 2004 ,pp. 715-719.

[171] S. P. Ghoshal, “Optimizations of PID gains by particle swarm optimizations in fuzzy based automatic generation control”, *Electric Power Syst. Res*., vol. 72, no. 3, Dec. 2004, pp. 203–212.

[172] L. Chun-Feng and J. Chia-Feng, “Evolutionary fuzzy control of flexible AC transmission system,” *Inst. Elect. Eng. Proc. Generation, Transmission Distrib.*, vol. 152, no. 4, 2005 ,pp. 441–448.

[173] R. F. Chang and C. N. Lu, “Feeder reconfiguration for load factor improvement,” in *Proc. IEEE Power Eng. Soc. Winter meeting*, vol. 2, 2002, pp. 980-984.

[174] C. C. Shen and C. N. Lu, “Feeder reconfiguration for power quality requirement and feeder service quality matching,” in *Proc. IEEE/PES Transmission Distrib. Conf. Exhib*., vol. 1, 2002, pp. 226-231.

[175] S. Kannan, S. M. R. Slochanal, P. Subbaraj, and N. P. Padhy, “Application of particle swarm optimization technique and its variants to generation expansion planning problem”, *Electric Power Syst. Res.*, vol. 70, no. 3, Aug. 2004 ,pp. 203-210.

[176] P. S. Sensarma, M. Rahmani, and A. Carvalho, “A comprehensive method for optimal expansion planning using particle swarm

optimization," in Proc. IEEE Power Eng. Soc. Winter Meeting, vol. 2, 2002, pp. 1317-1322.

[177] J. Aghaei, M.A. Akbari, A. Roosta, "Integrated renewable-conventional generation expansion planning using multiobjective framework", *Generation, Transmission & Distribution, IET* , vol.6, no.8, August 2012, pp.773-784.

[178] M.F. Shaaban, E.F. El-Saadany, "Accommodating High Penetrations of PEVs and Renewable DG Considering Uncertainties in Distribution Systems" *IEEE Transactions on Power Systems*, vol.29, no.1, Jan. 2014, pp. 259-270.

[179] A. Haji, B.J. Eini, M. Mirvazand, M. Safari, "Comparison between different multi-objective approaches to distribution network planning", *22nd International Conference and Exhibition on Electricity Distribution, 2013,* pp.1-4.

[180] G. Cartina, G. Grigoras ,E. Bobric, "Power system analysis using MATLAB toolboxes", *6th International conference on electromechanical and power systems*, 2007.

[181] N.M. Pindoriya, S.N Singh, K. Y. Lee, "A comprehensive survey on multi-objective evolutionary optimization in power system applications", *Power and Energy Society General Meeting, 2010,* pp.1-8.

[182] M. Caramia, P. Dell'Olmo," Multi-objective optimization and Pareto-optimal solutions" in *Multi-objective Management in Freight Logistics,* New York: Springer, 2008, p. 12.

[183] V. Chankong, Y. Y. Haimes, *Multiobjective Decision Making: Theory and Methodology*. Elsevier: New York, 1983.

[184] Y. Song; M. Irving, "Optimisation techniques for electrical power systems. II. Heuristic optimisation methods", *Power Engineering Journal*, vol.15, no.3, June 2001, pp.151-160.

[185] A.Haji, B.J. Eini,M. Mirvazand, M. Safari, "Comparison between different multi-objective approaches to distribution network planning," *22nd International Conference and Exhibition on Electricity Distribution, 2013* , pp.1-4.

[186] M. Glavic, L. Wehenkel,” Interior Point Methods, a short survey of applications to power systems, and research opportunities”, Technical report, Feb. 2004.

[187] P. E. McSharry, S. Bouwman, and G. Bloemhof, "Probabilistic forecasts of the magnitude and timing of peak electricity demand", *IEEE Transactions Power Systems*, vol. 20, , 2005 ,pp. 1166-1172.

[188] E. Gonzalez-Romera, M.A. Jaramillo-Moran, D. Carmona-Fernandez, "Monthly Electric Energy Demand Forecasting Based on Trend Extraction”, *IEEE Transactions on Power Systems*, vol. 21, 2006 , pp. 1946-1953.

[189] L.F. Ochoa, A. Padilha-Feltrin, G.P. Harrison, "Evaluating distributed generation impacts with a multiobjective index," *Power Delivery, IEEE Transactions*, vol.21, no.3, 2006, pp.1452-1458.

[190] L.F. Ochoa, A. Padilha-Feltrin, G.P. Harrison, "Evaluating Distributed Time-Varying Generation Through a Multi-objective Index", *IEEE Transactions on Power Delivery*, vol.23, no.2, 2008, pp.1132-1138

[191] B. Borkowska, “Probabilistic load flow”, *IEEE Transactions on Power Apparatus and Systems*, no. 3, 1974, pp. 752 -759.

[192] T. Cui, F. Franchetti, "A Quasi-Monte Carlo approach for radial distribution system probabilistic load flow", *Innovative Smart Grid Technologies (ISGT), IEEE PES* ,2013, pp.1-6.

[193] T. Williams, C. Crawford, "Probabilistic Load Flow Modeling Comparing Maximum Entropy and Gram-Charlier Probability Density Function Reconstructions", *IEEE Transactions on Power Systems* , vol.28, no.1, 2013, pp. 272-280.

[194] P. Chen, Z. Chen,B. Bak-Jensen, "Probabilistic load flow: A review", *Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies,* 2008, pp.1586-1591.

[195] N. Khalesi, N. Rezaei, M.R. Haghifam, “DG allocation with application of dynamic programming for loss reduction and reliability improvement”, *International Journal of Electrical Power & Energy Systems*, vol. 33, iss. 2, 2011, pp. 288-295.

[196] M. R. AlRashidi, M. F. AlHajri, "Proper planning of multiple distributed generation sources using heuristic approach", *Modeling, Simulation and Applied Optimization 4th International Conference*, 2011, pp.1-5.

[197] RP. Payasi, AK Singh ,D Singh “Review of distributed generation planning: objectives, constraints, and algorithms” *International Journal of Engineering, Science and Technology,* 2011 pp.133-153.

[198] K.E Holbert, G. T. Heydt, "Prospects for dynamic transmission circuit ratings", *Circuits and Systems. IEEE International Symposium*, vol.3, 2001, pp. 205-208.

[199] S. Gill, E. Barbour, I. A. G. Wilson, D. Infield, "Maximising revenue for non-firm distributed wind generation with energy storage in an active management scheme", *IET Conference on Renewable Power Generation*, 2011, pp.1-6.

[200] J.P. Barton, D.G. Infield, "Energy storage and its use with intermittent renewable energy", *IEEE Transactions on Energy Conversion,* vol.19, no.2, 2004, pp. 441-448.

[201] H. L. Willis, Cost and economic evaluation in *Power distribution planning reference book*. New York: Marcel Dekker , 2004, pp 142-155.

[202] W. El-khattam,Y. Hegazy, M. Salama, "An integrated distributed generation optimization model for distribution system planning," *IEEE Power Engineering Society General Meeting*, vol.20, no. 2, 2005 pp.1158-1165.

[203] L.S. Oliveira ,S.F.P. Saramago, “Multiobjective Optimization Techniques Applied to Engineering Problems”, *Journal of the Brazilian Society of Mechanical Sciences and Engineering,* 2010 ,pp. 94-104.

[204] K. Nara, A. Shiose, M. Kitagawa, T. Ishihara, "Implementation of genetic algorithm for distribution systems loss minimum reconfiguration", *IEEE Transactions on Power Systems*, vol.7, no.3, ,1992, pp.1044-1051.

[205] A. C C. Coello, G.B. Lamont, D.A.V. Veldhuizen, Structures of various MOEA in *Evolutionary algorithms for solving multi-objective problems,* New York: Springer, 2007, pp. 92-94.

[206] K.F. Man, K.S. Tang,S. Kwang , Introuction, background and biological inspiration *in Genetic Algorithms: Concepts and Designs,* London:Springer, 2001, p. 10.

[207] M. Srinivas , L. M. Patnaik,” Genetic algorithms: A survey”. *IEEE Computer*, vol27, no.6, 1994.

[208] R.D. Zimmerman, C. E. Murillo-Sanchez (2015), *Matpower User’s Manual* [Online]. Available: http://www.pserc.cornell.edu/matpower/manual.pdf

[209] K. Deb, “Multi-Objective Optimization using Evolutionary Algorithms”, Singapore: John Wiley & Sons, 2001, pp. 171-180.

[210] (2015), IEEE 14 power systems test case archive [Online] Available: http://www.ee.washington.edu/research/pstca/pf14/pg_tca14bus.htm

[211] P. A. Lipka, R.P. O’Neill, S. Oren, “Developing Line Current magnitude Constraints for IEEE Test Problems”, 2014.

[212] S. Balaraman, N. Kamaraj, “Congestion management using hybrid particle swarm optimisation technique”, Journal of Electrical Systems, 2011, pp. 54-70.

[213] E. Davey, C. Jones, A. Foster, F. Ewing, “UK renewable energy roadmap”, Department of Energy and Climate Change, Nov. 2013.

[214] I. Zamani, M. Irving, “A novel approach to distributed energy resource planning using NSGA-II”, in *Proc 47th International Universities Power Engineering Conference,* 2012.

[215] M. Scheepers, “Regulatory Improvements for Effective Integration of Distributed Generationinto Electricity Distribution Networks”, Tech Rep. 2007.

[216] *Minimize Rastrigin's Function* [Online]. Available: http://uk.mathworks.com/help/gads/example-rastrigins-function.html .

[217] D. Bingham, S. Surjanovic (2015), *Virtual Library of Simulation Experiments: Griewank function* [Online]. Available: http://www.sfu.ca/~ssurjano/griewank.html .

[218] D. Bingham, S. Surjanovic (2015), *Virtual Library of Simulation Experiments: Sphere function* [Online]. Available: http://www.sfu.ca/~ssurjano/spheref.html.

[219] T. Goel, "Elitist Non-dominated Sorting Genetic Algorithm: NSGA-II", Lecture note, University of Florida, 2011.

Appendix A

IEEE 14 Bus Data

S_{base}=100 MVA

1- Demand (Load) Data in MW and MVAr

bus number	type	Pd	Qd	Gs	Bs
1	3	0	0	0	0
2	2	21.7	12.7	0	0
3	2	94.2	19	0	0
4	1	47.8	-3.9	0	0
5	1	7.6	1.6	0	0
6	2	11.2	7.5	0	0
7	1	0	0	0	0
8	2	0	0	0	0
9	1	29.5	16.6	0	19
10	1	9	5.8	0	0
11	1	3.5	1.8	0	0
12	1	6.1	1.6	0	0
13	1	13.5	5.8	0	0
14	1	14.9	5	0	0

2- Generation Data in MW and MVAr

Bus	Pg	Qg
1	232.4	-16.9
2	40	42.4
3	0	23.4
6	0	12.2
8	0	17.4

3- Branch Data (R and X in Per Unit)

from bus	to bus	R	X
1	2	0.01938	0.05917
1	5	0.05403	0.22304
2	3	0.04699	0.19797
2	4	0.05811	0.17632
2	5	0.05695	0.17388
3	4	0.06701	0.17103

4	5	0.01335	0.04211
4	7	0	0.20912
4	9	0	0.55618
5	6	0	0.25202
6	11	0.09498	0.1989
6	12	0.12291	0.25581
6	13	0.06615	0.13027
7	8	0	0.17615
7	9	0	0.11001
9	10	0.03181	0.0845
9	14	0.12711	0.27038
10	11	0.08205	0.19207
12	13	0.22092	0.19988
13	14	0.17093	0.34802

Appendix B

IEEE 30 Bus Data

S_{base}=100 MVA

1- Demand (Load) Data in MW and MVAr

Bus number	Type	Pd	Qd	Gs	Bs
1	3	0	0	0	0
2	2	21.7	12.7	0	0
3	1	2.4	1.2	0	0
4	1	7.6	1.6	0	0
5	1	0	0	0	0.19
6	1	0	0	0	0
7	1	22.8	10.9	0	0
8	1	30	30	0	0
9	1	0	0	0	0
10	1	5.8	2	0	0
11	1	0	0	0	0
12	1	11.2	7.5	0	0
13	2	0	0	0	0
14	1	6.2	1.6	0	0
15	1	8.2	2.5	0	0
16	1	3.5	1.8	0	0
17	1	9	5.8	0	0
18	1	3.2	0.9	0	0
19	1	9.5	3.4	0	0
20	1	2.2	0.7	0	0
21	1	17.5	11.2	0	0
22	2	0	0	0	0
23	2	3.2	1.6	0	0
24	1	8.7	6.7	0	0.04
25	1	0	0	0	0
26	1	3.5	2.3	0	0
27	2	0	0	0	0
28	1	0	0	0	0
29	1	2.4	0.9	0	0
30	1	10.6	1.9	0	0

2- Generation Data

Bus	Pg	Qg
1	23.54	0
2	60.97	0
22	21.59	0
27	26.91	0
23	19.2	0
13	37	0

3- Branch Data (R and X in Per Unit)

From bus	To bus	R	X
1	2	0.02	0.06
1	3	0.05	0.19
2	4	0.06	0.17
3	4	0.01	0.04
2	5	0.05	0.2
2	6	0.06	0.18
4	6	0.01	0.04
5	7	0.05	0.12
6	7	0.03	0.08
6	8	0.01	0.04
6	9	0	0.21
6	10	0	0.56
9	11	0	0.21
9	10	0	0.11
4	12	0	0.26
12	13	0	0.14
12	14	0.12	0.26
12	15	0.07	0.13
12	16	0.09	0.2
14	15	0.22	0.2
16	17	0.08	0.19
15	18	0.11	0.22
18	19	0.06	0.13
19	20	0.03	0.07
10	20	0.09	0.21
10	17	0.03	0.08
10	21	0.03	0.07
10	22	0.07	0.15
21	22	0.01	0.02
15	23	0.1	0.2

22	24	0.12	0.18
23	24	0.13	0.27
24	25	0.19	0.33
25	26	0.25	0.38
25	27	0.11	0.21
28	27	0	0.4
27	29	0.22	0.42
27	30	0.32	0.6
29	30	0.24	0.45
8	28	0.06	0.2
6	28	0.02	0.06

Appendix C

IEEE 118 Bus Data

S_{base}=100 MVA

1- Demand (Load) Data in MW and MVAr

Bus number	Type	Pd	Qd	Gs	Bs
1	2	51	27	0	0
2	1	20	9	0	0
3	1	39	10	0	0
4	2	39	12	0	0
5	1	0	0	0	-40
6	2	52	22	0	0
7	1	19	2	0	0
8	2	28	0	0	0
9	1	0	0	0	0
10	2	0	0	0	0
11	1	70	23	0	0
12	2	47	10	0	0
13	1	34	16	0	0
14	1	14	1	0	0
15	2	90	30	0	0
16	1	25	10	0	0
17	1	11	3	0	0
18	2	60	34	0	0
19	2	45	25	0	0
20	1	18	3	0	0
21	1	14	8	0	0
22	1	10	5	0	0
23	1	7	3	0	0
24	2	13	0	0	0
25	2	0	0	0	0
26	2	0	0	0	0
27	2	71	13	0	0
28	1	17	7	0	0
29	1	24	4	0	0
30	1	0	0	0	0
31	2	43	27	0	0
32	2	59	23	0	0
33	1	23	9	0	0
34	2	59	26	0	14
35	1	33	9	0	0

36	2	31	17	0	0
37	1	0	0	0	-25
38	1	0	0	0	0
39	1	27	11	0	0
40	2	66	23	0	0
41	1	37	10	0	0
42	2	96	23	0	0
43	1	18	7	0	0
44	1	16	8	0	10
45	1	53	22	0	10
46	2	28	10	0	10
47	1	34	0	0	0
48	1	20	11	0	15
49	2	87	30	0	0
50	1	17	4	0	0
51	1	17	8	0	0
52	1	18	5	0	0
53	1	23	11	0	0
54	2	113	32	0	0
55	2	63	22	0	0
56	2	84	18	0	0
57	1	12	3	0	0
58	1	12	3	0	0
59	2	277	113	0	0
60	1	78	3	0	0
61	2	0	0	0	0
62	2	77	14	0	0
63	1	0	0	0	0
64	1	0	0	0	0
65	2	0	0	0	0
66	2	39	18	0	0
67	1	28	7	0	0
68	1	0	0	0	0
69	3	0	0	0	0
70	2	66	20	0	0
71	1	0	0	0	0
72	2	12	0	0	0
73	2	6	0	0	0
74	2	68	27	0	12
75	1	47	11	0	0
76	2	68	36	0	0
77	2	61	28	0	0
78	1	71	26	0	0
79	1	39	32	0	20
80	2	130	26	0	0
81	1	0	0	0	0

82	1	54	27	0	20
83	1	20	10	0	10
84	1	11	7	0	0
85	2	24	15	0	0
86	1	21	10	0	0
87	2	0	0	0	0
88	1	48	10	0	0
89	2	0	0	0	0
90	2	163	42	0	0
91	2	10	0	0	0
92	2	65	10	0	0
93	1	12	7	0	0
94	1	30	16	0	0
95	1	42	31	0	0
96	1	38	15	0	0
97	1	15	9	0	0
98	1	34	8	0	0
99	2	42	0	0	0
100	2	37	18	0	0
101	1	22	15	0	0
102	1	5	3	0	0
103	2	23	16	0	0
104	2	38	25	0	0
105	2	31	26	0	20
106	1	43	16	0	0
107	2	50	12	0	6
108	1	2	1	0	0
109	1	8	3	0	0
110	2	39	30	0	6
111	2	0	0	0	0
112	2	68	13	0	0
113	2	6	0	0	0
114	1	8	3	0	0
115	1	22	7	0	0
116	2	184	0	0	0
117	1	20	8	0	0
118	1	33	15	0	0

2- Generation Data in MW and MVAr

Bus	Pg	Qg
1	0	0
4	0	0
6	0	0
8	0	0
10	450	0
12	85	0
15	0	0
18	0	0
19	0	0
24	0	0
25	220	0
26	314	0
27	0	0
31	7	0
32	0	0
34	0	0
36	0	0
40	0	0
42	0	0
46	19	0
49	204	0
54	48	0
55	0	0
56	0	0
59	155	0
61	160	0
62	0	0
65	391	0
66	392	0
69	516.4	0
70	0	0
72	0	0
73	0	0
74	0	0
76	0	0
77	0	0
80	477	0
85	0	0
87	4	0
89	607	0
90	0	0
91	0	0

92	0	0
99	0	0
100	252	0
103	40	0
104	0	0
105	0	0
107	0	0
110	0	0
111	36	0
112	0	0
113	0	0
116	0	0

3- Branch Data (R and X in Per Unit)

From bus	To bus	R	X
1	2	0.0303	0.0999
1	3	0.0129	0.0424
4	5	0.00176	0.00798
3	5	0.0241	0.108
5	6	0.0119	0.054
6	7	0.00459	0.0208
8	9	0.00244	0.0305
8	5	0	0.0267
9	10	0.00258	0.0322
4	11	0.0209	0.0688
5	11	0.0203	0.0682
11	12	0.00595	0.0196
2	12	0.0187	0.0616
3	12	0.0484	0.16
7	12	0.00862	0.034
11	13	0.02225	0.0731
12	14	0.0215	0.0707
13	15	0.0744	0.2444
14	15	0.0595	0.195
12	16	0.0212	0.0834
15	17	0.0132	0.0437
16	17	0.0454	0.1801
17	18	0.0123	0.0505
18	19	0.01119	0.0493
19	20	0.0252	0.117
15	19	0.012	0.0394
20	21	0.0183	0.0849
21	22	0.0209	0.097

22	23	0.0342	0.159
23	24	0.0135	0.0492
23	25	0.0156	0.08
26	25	0	0.0382
25	27	0.0318	0.163
27	28	0.01913	0.0855
28	29	0.0237	0.0943
30	17	0	0.0388
8	30	0.00431	0.0504
26	30	0.00799	0.086
17	31	0.0474	0.1563
29	31	0.0108	0.0331
23	32	0.0317	0.1153
31	32	0.0298	0.0985
27	32	0.0229	0.0755
15	33	0.038	0.1244
19	34	0.0752	0.247
35	36	0.00224	0.0102
35	37	0.011	0.0497
33	37	0.0415	0.142
34	36	0.00871	0.0268
34	37	0.00256	0.0094
38	37	0	0.0375
37	39	0.0321	0.106
37	40	0.0593	0.168
30	38	0.00464	0.054
39	40	0.0184	0.0605
40	41	0.0145	0.0487
40	42	0.0555	0.183
41	42	0.041	0.135
43	44	0.0608	0.2454
34	43	0.0413	0.1681
44	45	0.0224	0.0901
45	46	0.04	0.1356
46	47	0.038	0.127
46	48	0.0601	0.189
47	49	0.0191	0.0625
42	49	0.0715	0.323
42	49	0.0715	0.323
45	49	0.0684	0.186
48	49	0.0179	0.0505
49	50	0.0267	0.0752
49	51	0.0486	0.137
51	52	0.0203	0.0588
52	53	0.0405	0.1635
53	54	0.0263	0.122

49	54	0.073	0.289
49	54	0.0869	0.291
54	55	0.0169	0.0707
54	56	0.00275	0.00955
55	56	0.00488	0.0151
56	57	0.0343	0.0966
50	57	0.0474	0.134
56	58	0.0343	0.0966
51	58	0.0255	0.0719
54	59	0.0503	0.2293
56	59	0.0825	0.251
56	59	0.0803	0.239
55	59	0.04739	0.2158
59	60	0.0317	0.145
59	61	0.0328	0.15
60	61	0.00264	0.0135
60	62	0.0123	0.0561
61	62	0.00824	0.0376
63	59	0	0.0386
63	64	0.00172	0.02
64	61	0	0.0268
38	65	0.00901	0.0986
64	65	0.00269	0.0302
49	66	0.018	0.0919
49	66	0.018	0.0919
62	66	0.0482	0.218
62	67	0.0258	0.117
65	66	0	0.037
66	67	0.0224	0.1015
65	68	0.00138	0.016
47	69	0.0844	0.2778
49	69	0.0985	0.324
68	69	0	0.037
69	70	0.03	0.127
24	70	0.00221	0.4115
70	71	0.00882	0.0355
24	72	0.0488	0.196
71	72	0.0446	0.18
71	73	0.00866	0.0454
70	74	0.0401	0.1323
70	75	0.0428	0.141
69	75	0.0405	0.122
74	75	0.0123	0.0406
76	77	0.0444	0.148
69	77	0.0309	0.101
75	77	0.0601	0.1999

77	78	0.00376	0.0124
78	79	0.00546	0.0244
77	80	0.017	0.0485
77	80	0.0294	0.105
79	80	0.0156	0.0704
68	81	0.00175	0.0202
81	80	0	0.037
77	82	0.0298	0.0853
82	83	0.0112	0.03665
83	84	0.0625	0.132
83	85	0.043	0.148
84	85	0.0302	0.0641
85	86	0.035	0.123
86	87	0.02828	0.2074
85	88	0.02	0.102
85	89	0.0239	0.173
88	89	0.0139	0.0712
89	90	0.0518	0.188
89	90	0.0238	0.0997
90	91	0.0254	0.0836
89	92	0.0099	0.0505
89	92	0.0393	0.1581
91	92	0.0387	0.1272
92	93	0.0258	0.0848
92	94	0.0481	0.158
93	94	0.0223	0.0732
94	95	0.0132	0.0434
80	96	0.0356	0.182
82	96	0.0162	0.053
94	96	0.0269	0.0869
80	97	0.0183	0.0934
80	98	0.0238	0.108
80	99	0.0454	0.206
92	100	0.0648	0.295
94	100	0.0178	0.058
95	96	0.0171	0.0547
96	97	0.0173	0.0885
98	100	0.0397	0.179
99	100	0.018	0.0813
100	101	0.0277	0.1262
92	102	0.0123	0.0559
101	102	0.0246	0.112
100	103	0.016	0.0525
100	104	0.0451	0.204
103	104	0.0466	0.1584
103	105	0.0535	0.1625

100	106	0.0605	0.229
104	105	0.00994	0.0378
105	106	0.014	0.0547
105	107	0.053	0.183
105	108	0.0261	0.0703
106	107	0.053	0.183
108	109	0.0105	0.0288
103	110	0.03906	0.1813
109	110	0.0278	0.0762
110	111	0.022	0.0755
110	112	0.0247	0.064
17	113	0.00913	0.0301
32	113	0.0615	0.203
32	114	0.0135	0.0612
27	115	0.0164	0.0741
114	115	0.0023	0.0104
68	116	0.00034	0.00405
12	117	0.0329	0.14
75	118	0.0145	0.0481
76	118	0.0164	0.0544