DISTRIBUTED GENERATION ALLOCATION FOR POWER LOSS MINIMIZATION AND VOLTAGE IMPROVEMENT OF RADIAL DISTRIBUTION SYSTEMS USING GENETIC ALGORITHM

By

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled "**Distributed Generation Allocation For Power Loss Minimization And Voltage Improvement Of Radial Distribution Systems Using Genetic Algorithm**" in partial fulfilment of the requirements for the award of **Master Of Technology** degree in **Electrical Engineering** submitted in Electrical Engineering Department of National Institute of Technology, Rourkela is an authentic record of my own work carried out under the supervision of Dr. Sanjib Ganguly, Assistant Professor, Department of Electrical Engineering.

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

(Dipanjan Samajpati)

This is certify that the above statement made by candidate is correct and true to best of my knowledge.

(Dr. Sanjib Ganguly)

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This thesis is dedicated

To the soul of my Father and beloved Mother,
May God bless them and elongate them live in his obedience!!

To my best friend Smarani,
May God bless her and give her a sweet, happy, deserving trustful life!!

---Dipanjan Samajpati

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Dipanjan Samajpati

ABSTRACT

Numerous advantages attained by integrating Distributed Generation (DG) in distribution systems. These advantages include decreasing power losses and improving voltage profiles. Such benefits can be achieved and enhanced if DGs are optimally sized and located in the systems. This theses presents a distribution generation (DG) allocation strategy to improve node voltage and power loss of radial distribution systems using genetic algorithm (GA). The objective is to minimize active power losses while keep the voltage profiles in the network within specified limit. In this thesis, the optimal DG placement and sizing problem is investigated using two approaches. First, the optimization problem is treated as single-objective optimization problem, where the system's active power losses are considered as the objective to be minimized. Secondly, the problem is tackled as a multi-objective one, focusing on total power loss as well as voltage profile of the networks. This approach finds optimal DG active power and optimal OLTC position for tap changing transformer. Also uncertainty in load and generation are considered. Thus, in this work, the load demand at each node and the DG power generation at candidate nodes are considered as a possibilistic variable represented by two different triangular fuzzy number. A 69-node radial distribution system and 52-node practical radial systems are used to demonstrate the effectiveness of the proposed methods. The simulation results shows that reduction of power loss in distribution system is possible and all node voltages variation can be achieved within the required limit if DG are optimally placed in the system. Induction DG placement into the distribution system also give a better performance from capacitor bank placement. In modern load growth scenario uncertainty load and generation model shows that reduction of power loss in distribution system is possible and all node voltages variation can be achieved within the required limit without violating the thermal limit of the system.

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LIST OF ABBREVIATIONS AND SYMBOLS USED

P_{loss}	Power loss of the network
R_i	The resistance of *i-th* branch.
S_i	The complex power at *i-th* node.
P_i	The real power at *i-th* node.
Q_i	The reactive power at i-*th* node.
V_i	*I-th* node voltage.
I_i	*I-th* node equivalent current injection.
V_i^k	The node voltage at the *k-th* iteration for *i-th* node.
I_j^k	The equivalent current injection at the *k-th* iteration for *i-th* node.
I_j^r	the real parts of the equivalent current injection at the *k-th* iteration for *i-th* node.
I_j^i	the imaginary parts of the equivalent current injection at the *k-th* iteration for *i-th* node.
k_v	Voltage weighting factor.
k_p	Power loss weighting factor.
V_{sub}	Main sub-station voltage.
$V_i^{without\_DG}$	Voltage of i-th node of RDS without DG.
$V_i^{with\_DG}$	Voltage of i-th node of RDS with DG.
$P_{loss}^{without\_DG}$	Total power loss of RDS without DG.
$P_{loss}^{with\_DG}$	Total power loss of RDS with DG.
N_L	Number of distribution network branch available in the network.
N_B	Number of distribution network node available in the network.
V_{var}	Voltage variation of any node of RDS respect to sub-station voltage.
$I_{L\_\max\_i}$	Maximum current level of i-th branch.
I_{L_i}	Actual current of i-th branch.

CHAPTER-1

INTRODUCTION AND LITERATURE REVIEW

1.1 INTRODUCTION

The modern power distribution network is constantly being faced with an ever growing load demand, this increasing load is resulting into increased burden and reduced voltage [1]. The distribution network also has a typical feature that the voltage at nodes (nodes) reduces if moved away from substation. This decrease in voltage is mainly due to insufficient amount of reactive power. Even in certain industrial area critical loading, it may lead to voltage collapse. Thus to improve the voltage profile and to avoid voltage collapse reactive compensation is required [1-2]. The X/R ratio for distribution levels is low compared to transmission levels, causing high power losses and a drop in voltage magnitude along radial distribution lines [1-3]. It is well known that loss in a distribution networks are significantly high compared to that in a transmission networks. Such non-negligible losses have a direct impact on the financial issues and overall efficiency of distribution utilities. The need of improving the overall efficiency of power delivery has forced the power utilities to reduce the losses at distribution level. Many arrangements can be worked out to reduce these losses like network reconfiguration, shunt capacitor placement, distributed generator placement etc. [1-3]. The distributed generators supply part of active power demand, thereby reducing the current and MVA in lines. Installation of distributed generators on distribution network will help in reducing energy losses, peak demand losses and improvement in the networks voltage profile, networks stability and power factor of the networks [3, 4][9-10].

Distributed generation (DG) technologies under smart grid concept forms the backbone of our world Electric distribution networks [5] [10]. These DG technologies are classified into two categories: (i) renewable energy sources (RES) and (ii) fossil fuel-based sources. Renewable energy source (RES) based DGs are wind turbines, photovoltaic, biomass, geothermal, small hydro, etc. Fossil fuel based DGs are the internal combustion engines (IC), combustion turbines and fuel cells [3] [6-7]. Environmental, economic and technical factors have a huge role in DG development. In accord with the Kyoto agreement on climate change, many efforts to reduce carbon emissions have been taken, and as a result of which, the penetration of DGs in distribution systems rises [8]. Presence of Distributed generation in distribution networks is a momentous challenge in terms of technical and safety issues [12-14]. Thus, it is critical to evaluate the technical impacts of DG in power networks. Thus, the generators are needed to be connected in distributed systems in such a manner that it avoids degradation of power quality and reliability. Evaluation of the technical impacts of DG in the power networks is very critical and laborious. Inadequate allocation of DG in terms of its location and capacity may lead to increase in fault currents, causes voltage variations, interfere in voltage-control processes, diminish or increase losses, increase system capital and operating costs, etc. [13]. Moreover, installing DG units is not straightforward, and thus the placement and sizing of DG units should be carefully addressed [13-14]. Investigating this optimization problem is the major motivation of the present thesis research.

DG allocation is basically a complex combinatorial optimization issue which requires concurrent optimization of multiple objectives [15], for instance minimizations of real and reactive power losses, node voltage deviation, carbon emanation, line loading, and short circuit capacity and maximization of network reliability etc. The goal is to determine the optimal location(s) and size(s) of DG units in a distribution network. The optimization is carried out under the constraints of maximum DG sizes, thermal limit of network branches, and voltage limit of the nodes [14-15]. In [17], sensitivity analysis had been used for finding the optimal location of DG. In [18], the optimal location of DGs was predicted by finding V-index. In [19], Loss sensitivity factor had been used for finding the optimal location of DGs. There are numerous optimization techniques used in the literature. In [16], an analytical approach to determine the optimal location of DG is presented. In most of the current works, population based evolutionary algorithms are used as solution strategies. This includes genetic algorithm (GA) [20-24], evolutionary programming [25], and particle swarm optimization [10] [26-29] etc. The advantages of population-based meta-heuristics algorithms such as GA and PSO are that a set of non-dominated solutions can be found in a single run because of their multi-point search capacity. They are also less prone to dimensionality problems; however, convergence is not always guaranteed.

In most of the planning models, the optimal distribution network is determined based on a deterministic load demand which is usually obtained from a load forecast. The optimal DG power generation of a distribution network is determined based on the DG generation (i.e., electric utilities and customers) and weather forecast in the form of wind or solar power generation. However, such a forecast is always subject to some error. Since the operating conditions (e.g. node voltage, branch current, illumination of sun, wind speed, etc.) of any distribution network depend on the load, a network operating with loads that differ from the nominal ones may be subject to violations of the acceptable operating conditions [1-3] [43]. Also the placement of the DG units mainly the Renewable energy sources placement, is affected by several factors such as wind speed, solar irradiation, environmental factors, geographical topography, political factors, etc. For example, wind generators or turbines cannot be installed near residential areas, because of the interference in the form of public reactions and legislations from environmental organisations. Another issue is application of the plug-in electric vehicle (PEV) which is being paid more attention to [44-46]. However, there are several factors or uncertainties that can possibly lead to probable risks in determining the optimal siting and sizing of DGs in distribution system planning [47]. Some of the uncertainties are possibilistic output power of a PEV due to its alteration of charging/discharging schedule [48-50], wind power unit due to frequent variable wind speed, from a solar generating source due to the possibilistic illumination intensity, volatile fuel prices and future uncertain load growth [51-52]. The most essential uncertainty to account for the time-varying characteristics of both generation and demand of power are these increasing penetrations of variable renewable generators with wind power [47] [53], being the most noteworthy of them.

1.2 OBJECTIVE OF THE WORK

An innovative proposal for DG power management approach incorporating optimization algorithm for a group of DG units is depicted in this work. A recent load flow technique (i.e. Forward/Backward load flow method) for a radial distribution using BIBC and BCBV matrix has been used. The objective functions formulated in this work are minimizations of network power loss and node voltage deviation. In this study, load demand uncertainty (LDU) and DG power generation uncertainty (PGU) is incorporated into network planning to investigate its overall influence on planned networks. The load demand and the generation uncertainties are modelled by triangular fuzzy numbers, providing degrees of membership to all possible values of the load demand and DG power generation for each and candidate node respectively. The fuzzified objective functions are defuzzified using fuzzy removal technique so as to compare two solutions. GA based on adaptive crossover and mutation probabilities is used as the solution strategy. An adaptive GA is also proposed for DG allocation problem. Two different types of DG units are considered: (a) synchronous generators and (b) induction generators. Their performances are compared. The results obtained with multiple simulation runs are shown and statistically analysed. The simulation results of an IEEE 69-node reliability test network [24] [35] and a 52-node practical Indian network [34] are shown.

1.3 LITERATURE REVIEW

1.3.1 Distribution Networks and Distributed Generation

Classically, most distribution systems (DSs) are radial in nature, contain only one power source, and serve residential, commercial and industrial loads. DSs are also operated at the lowest voltage levels in the overall power networks [1]. Power is delivered in bulk to substations. The substation is usually where the transmission and distribution networks meet. The backbone of the distribution networks typically is comprised of 3-phase mains. Laterals are tapped off these mains and are usually single-phase (unless 3-phase service is required by a customer) [1-2]. In addition, the lines used for DSs tend to have a higher resistance to impedance ratio (R/X) than the lines in transmission networks [2]. The modern power distribution network is constantly being faced with a very rapid growing load demand, this increasing load is resulting into increased burden and reduced voltage also effect on the operation, planning, technical and safety issues of distribution networks [9-11]. This power losses in distribution networks have become the most concerned issue in power losses analysis in any power networks. In the effort of reducing power losses within distribution networks, reactive power compensation has become increasingly important as it affects the operational, economical and quality of service for electric power networks [10-11]. The planning should be such that the designed system should economically and reliably take care of spatial and temporal load growth, and service area expansion in the planning horizon [12-13]. In [12], various distribution networks planning models presented. The proposed models are grouped in a three-level classification structure starting with two broad categories, i.e., planning without and with reliability considerations. Planning of a distribution system relies on upon the load flow study. The load flow will be imperative for the investigation of distribution networks, to research the issues identified with planning, outline and the operation and control. Thusly, the load flow result of distribution networks ought to have ronodet and time proficient qualities. The load flow for distribution system is not alike transmission system due to some in born characteristics of its own. There are few techniques are available in literature. Ghosh and Das [68] proposed a method for the load flow of radial distribution network using the evaluation based on algebraic expression of receiving end voltage. Dharmasa et al. [69] present, non-iterative load flow solution for voltage improvement by Tap changer Transformer in the distribution networks. Teng et al. [70] has proposed the load flow of radial distribution networks employing node-injection to branch-current (BIBC) and branch-current to node-voltage (BCBV) matrices.

With the deregulation of energy markets, escalating costs of fossil fuels, and socio-environmental pressures, power networks planners are starting to turn away from the centralized power networks topology by installing smaller, renewable-powered generators at the distribution level [3-5] which is known as distributed generation. These DG technologies are classified into two categories: (i) renewable energy sources (RES) and (ii) fossil fuel-based sources. Renewable energy source (RES) based DGs are wind turbines, photovoltaic, biomass, geothermal, small hydro, etc. Fossil fuel based DGs are the internal combustion engines (IC), combustion turbines and fuel cells [3] [6-7] [37]. Distributed generators (DGs) have the advantages of having low environmental emissions, being more flexible in installation and with shorter gestation periods [37]. The technologies behind these renewable-powered generators are evolving to make these generators more utility-friendly (and thus more economical). Some of the DG technologies compete with conventional centralized generation technologies in operational aspects and cost. DG allocation in distribution system is basically a complex combinatorial optimization issue which requires concurrent optimization of multiple objectives [15], for instance minimizations of real and reactive power losses, node voltage deviation, carbon emanation, line loading, and short circuit capacity and maximization of network reliability etc. Presently, a large number of research papers are available on the subject of the DG allocation for power loss, voltage improvement, etc. [5-11] [17-18] [30-34]. Kashem et al. [9] presented a sensitivity indices to indicate the changes in power losses with respect to DG current injection. I Erlich et al. [10] present a new design methodology for managing reactive power from a group of distributed generators placed on a radial distribution networks. In [17], sensitivity analysis had been used for finding the optimal location of DG. In [18], the optimal location of DGs was predicted by finding V-index. In [19], Loss sensitivity factor had been used for finding the optimal location of DGs.

More and more DGs are currently being integrated into the distribution networks which have affected the operation, planning, technical and safety issues of distribution networks [10-14]. For example, through power electronics, these smaller generators can produce and absorb reactive power [40-41]. This issue of reactive power support is of great concern for utilities, especially for WEGs [42]. Thus, it is critical to evaluate the technical impacts of DG in power networks. Thus, the generators are needed to be connected in distributed systems in such a manner that it avoids degradation of power quality and reliability. Evaluation of the technical impacts of DG in the power networks is very critical and laborious. Inadequate allocation of DG in terms of its location and capacity may lead to increase in fault currents, causes voltage variations, interfere in voltage-control processes, diminish or increase losses, increase system capital and operating costs, etc. [13]. Moreover, installing DG units is not straightforward, and thus the placement and sizing of DG units should be carefully addressed [13-14].

Optimization is a process by which we try to find out the best solution from set of available alternative. In DG allocation problem, DG locations and sizes must be optimize in such a way that it give most economical, efficient, technically sound distribution system. In general distribution system have many nodes and it is very hard to find out the optimal DG location and size by hand. There are numerous optimization techniques used in the literature. Among the different solution strategies deterministic algorithm such as dynamic programming, mixed integer programming, nonlinear programming and Benders decomposing have been used. In [16], an analytical approach to determine the optimal location of DG is presented. However, more recent studies have mostly used heuristic algorithms, such as fuzzy mathematical programming [43], a genetic algorithm (GA) [20-25], a Tabu search (TS) [54], an artificial immune system (AIS) and evolutionary programming [25], partial swarm optimization [10] [17] [26-29].The advantages of population-based meta-heuristics algorithms such as GA and PSO are that a set of non-dominated solutions can be found in a single run because of their multi-point search capacity. They are also less prone to dimensionality problems; however, convergence is not always guaranteed.

Genetic Algorithms offer a ‘one size fits all’ solution to problem solving involving search [75]. Unlike other conventional search alternatives, GA’s can be applied to most problems, only needing a good function specification to optimize and a good choice of representation and interpretation. This, coupled with the exponentially increasing speed/cost ratio of computers, makes them a choice to consider for any search problem.

Genetic Algorithms (GAs) are versatile exploratory hunt processes focused around the evolutionary ideas of characteristic choice and genetics. A genetic algorithm is a heuristically guided random search technique that concurrently evaluates thousands of postulated solutions. Biased random selection and mixing of the evaluated searches is then carried out in order to progress towards better solutions. The coding and manipulation of search data is based upon the operation of genetic DNA and the selection process is derived from Darwin's survival of the fittest'. Search data are usually coded as binary strings called chromosomes, which collectively form populations [75]. Evaluation is carried out over the whole population and involves the application of, often complex 'fitness' functions to the string of values (genes) within each chromosome. Typically, mixing involves recombining the data that are held in two chromosomes that are selected from the whole population.

The traditional crossover like partly matched crossover, order crossover and cycle crossover, etc. and mutation would make some unfeasible solution to be created. In the traditional crossover and mutation, crossover probability and mutation probability are not adaptive in nature and which have no flexibility. For this reason when a basic GA optimization process trapped in a local minima these crossover and mutation probability cannot emerge from the local minima and GA optimization give a premature result. There are numerous adaptive techniques used in the literature [76-76]. In [26], based on the mechanism of biological DNA genetic information and evolution, a modified genetic algorithm (MDNA-GA) is proposed. The proposed adaptive mutation probability is dynamically adjusted by considering a measure called Diversity Index (DI). It is defined to indicate the premature convergence degree of the population. In [77], an Improved Genetic Algorithm (IGA) is proposed. The self-adaptive process have been employed for crossover and mutation probability in order to improve crossover and mutation quality. In [78], an Improved Genetic Algorithm (IGA) based on hormone modulation mechanism is proposed in order to ensure to create a feasible solution, a new method for crossover operation is adopted, named, partheno-genetic operation (PGO). . The adaptive approaches proposed by Vedat Toğan and Ayşe T. Daloğlu [79] for crossover and mutation operator of the GA. The performance of genetic algorithms (GA) is affected by various factors such as coefficients and constants, genetic operators, parameters and some strategies. Member grouping and initial population strategies are also examples of factors. While the member grouping strategy is adopted to reduce the size of the problem, the initial population strategy have been applied to reduce the number of search to reach the optimum design in the solution space. In this study, two new self-adaptive member grouping strategies, and a new strategy to set the initial population have been discussed. Chaogai Xue, Lili Dong and Junjuan Liu [80] proposed an adaptive approaches for crossover and mutation operator of the GA optimize enterprise information system (EIS) structure based on time property.

1.3.2 Uncertainty in Distribution Planning

In most of the planning models, the optimal distribution network is determined based on a deterministic load demand which is usually obtained from a load forecast. The optimal DG power generation of a distribution network is determined based on the DG generation (i.e., electric utilities and customers) and weather forecast in the form of wind or solar power generation. However, such a forecast is always subject to some error. Since the operating conditions (e.g. node voltage, branch current, illumination of sun, wind speed, etc.) of any distribution network depend on the load, a network operating with loads that differ from the nominal ones may be subject to violations of the acceptable operating conditions [1-2] [43]. Also the placement of the DG units mainly the Renewable energy sources placement, is affected by several factors such as wind speed, solar irradiation, environmental factors, geographical topography, political factors, etc. For example, wind generators or turbines cannot be installed near residential areas, because of the interference in the form of public reactions and legislations from environmental organisations. Another issue is application of the plug-in electric vehicle (PEV) which is being paid more attention to [44-46]. However, there are several factors or uncertainties that can possibly lead to probable risks in determining the optimal siting and sizing of DGs in distribution system planning [47]. Some of the uncertainties are possibilistic output power of a PEV due to its alteration of charging/discharging schedule [48-50], wind power unit due to frequent variable wind speed, from a solar generating source due to the possibilistic illumination intensity, volatile fuel prices, uncertain electricity price and future uncertain load growth [51-52] [57]. The most essential uncertainty to account for the time-varying characteristics of both generation and demand of power are these increasing penetrations of variable renewable generators with wind power [43] [47] [53], being the most noteworthy of them. In [53], the multiple objective functions are aggregated to form a single objective function so as to optimize them. However, in [54], the multiple objectives are simultaneously optimized to obtain a set of non-dominated solutions, in which no solution is superior or inferior to others. The most of the approaches are based on the constant power load model, except in [43], in which voltage dependent load model is used.

1.4 ORGANIZATION OF THE REPORT

The work carried out in this Report has been summarized in six chapters.

The Chapter 2 highlights the brief introduction, summary of work carried out by various researchers, and the outline of the thesis is also given in this chapter. The Chapter 3 explains the Forward/Backward Load Flow Technique of distribution networks using BIBC and BCBV matrix, Distributed generator planning, Genetic Algorithm. The Chapter 4 briefly describes how to identify the candidate nodes for distributed generator placement, objective function for overall loss minimization of distribute on networks, steps for Distributed Generator (DG) Allocation using Genetic Algorithm, and results and discussion pertaining to various test cases. The Chapter 5 details the uncertainty in distribution planning. The conclusions and the scope of further work are detailed in Chapter 6.

CHAPTER-2

MODELLING AND ALLOCATION OF DG IN DISTRIBUTION NETWORKS

2.1 INTRODUCTION

Loss Minimization in power networks has assumed greater significance, in light of the fact that enormous amount of generated power is continuously squandered as losses. Studies have demonstrated that 70% of the aggregate networks losses are happening in the distribution networks, while transmission lines represent just 30% of the aggregate losses [1]. The pressure of enhancing the overall proficiency of power delivery has forced the power utilities to reduce the loss, particularly at the distribution level. The following approaches are embraced for reduction of distribution networks losses [1-2].

- Reinforcement of the feeders.
- Reactive power compensation.
- High voltage distribution networks.
- Grading of conductor.
- Feeder reconfiguration.
- Distributed Generator placement.

Smart grid concept is expected to become a backbone in Europe future electricity network [10]. In achieving a Smart Grid concept, a large number of distributed generators (DG) are needed inside distribution network which is prognosed to supply up to 40% of the distribution network's load demand. This substantial number of DG is obliged to take part in enhancing the security, reliability and quality of electricity supply by providing active power and other subordinate services such as regulating the voltage by providing their reactive supply to the network. One of the characteristics of future electricity network under smart grid idea is to have an efficient transmission and distribution network that will reduce line losses [3-9]. Minimizing losses inside power transport networks will being about easier utilization of fossil fuel consequently reduced emanation of air pollutant and greenhouse gasses. Coordinating of DG inside distribution network reduces power losses in light of the fact that some share of the required load current from upstream is generously reduce which result lower losses through line resistance. Further reduction of losses can be attained by intelligently managing reactive power from introduced DG [10].

2.2 DISTRIBUTION NETWORK POWER LOSSES

An active power loss in the line depends on magnitude of the current flows through the line and resistance of the line. In ac distribution circuit, due to electric and magnetic field produce by the flow of time varying current, inductance and capacitance might be noteworthy. At the point when current flow through these two components, reactive power which transmit no energy is produced. Reactive current flow in the line adds to extra power losses in addition to active power losses mention previously. Integration of DG already reduced active power losses because some portion of power from upstream is already reduced. Losses reduction can be further reduced by controlling the voltage profiles in the network. In conventional practice, capacitor banks are added in the distribution network to control the flow of this reactive power. These capacitor banks can be switched in and out using voltage regulating relay to deliver reactive power in steps but it lowered power quality delivered to the customer as it leads to step changes in node-bar voltage.

$$P_{loss}(x) = \sum_i 3\, I_i^2 R_i \qquad \forall i = N_L \tag{1.1}$$

2.3 DISTRIBUTED GENERATION

2.3.1 Operational and Planning Issues with DGs

Distributed Generators (DG) are crisply characterized as "electric power sources joined specifically to the distribution system or on the client side of the meter" [3]. This definition for the most part obliges a variety of technologies and execution crosswise over diverse utility structures, while evading the pitfalls of utilizing more stringent criteria focused around standards, for example, power ratings and power delivery area. Distribution planning includes the investigation of future power delivery needs and options, with an objective of creating a precise course of action of increases to the networks required to attain agreeable levels of service at a minimum overall cost [4]. Executing DGs in the distribution system has numerous profits, yet in the meantime it confronts numerous restrictions and limitations. DG units, being adaptable, could be built to meet immediate needs and later be scaled upwards in capacity to take care of future demand growth. Versatility permits DG units to reduce their capital and operations costs and therefore substantial capital is not tied up in investments or in their support infrastructure. Investment funds can likewise be accomplished since infrastructure updates, (for example, feeder capacity extensions) might be deferred or altogether eliminated. From a client perspective, funds may be gathered from the extra decision and flexibility that DGs permit with respect to energy purchases [3-6]. On the other hand, then again, installing DG in the distribution networks can also increase the complexity of networks planning. DG must be satisfactorily introduced and facilitated with the existing protective devices and schemes. Higher penetration levels of DG may cause conventional power flows to alter (reverse direction), since with generation from DG units, power may be injected at any point on the feeder. New planning systems must guarantee that feeders can suit changes in load configuration. These limitations and problems must be settled before picking DG as a planning alternative. Some of the associated issues in distribution networks with penetration of DG units are as discussed next.

2.3.2 DG Operation

There are numerous components influencing DG operation, for example, DG technologies, types, operational modes, and others. DGs installed in the distribution network can be owned, operated and controlled by either an electric utility or a customer. In the event that DG is utility-claimed, then its working cycle is well known as is controlled by the utility. The state of the DG working cycle relies on upon the motivation behind its utilization in the distribution system [3-9]. For example:

a) Limited operating time units for peak crest load shaving (Internal combustion engines, small fuel cell units).

b) Limited operating time units to impart the load to diverse operating cycles (Micro-turbines and fuel cells).

c) Base load power supply (Micro-turbines and large fuel cells).

d) Renewable energy units influenced by ecological conditions, for example, wind speed and sunlight respectively (Wind generators and solar cells)

On the other hand, customer-owned DG operating cycles are not known to the operators unless there is a unit commitment agreement between the electric utility and the customer, which is not very likely. Thus, small customer owned DG operating cycles are acknowledged to be capricious processes from the perspective of the electric utility. The utility has no control on their operation. This uncertainty changes the planning and operation problem from a deterministic problem to a non-deterministic one.

2.3.3 DG Siting

There are no agreeable limitations on location of DG units in the distribution system, as there are no geological limitations as on account of substations. Subsequently, the main limitations emerge from electrical necessities. In the event that the DG is client possessed then the utility has no control on its location in light of the fact that it is put at the client's site. In the event that the DG is utility-possessed then the choice of its location is focused around a few electrical factors, for example:

• Providing the required extra load demand

• Reducing networks losses

• Enhancing networks voltage profile and expanding substations capacities

Likewise, DG units must be put on feeders that don't affect the existing protective device co-ordinations and ratings.

2.3.4 DG Sizing

There are no clear guidelines on selecting the size and number of DG units to be introduced in the network. However, a few aspects can be guiding the choice of DG unit size selection:

a) To enhance the networks voltage profile and reduce power losses, it is sufficient to utilize DG units of aggregate capacity in the reach of 10-20% of the aggregate feeder demand [3]. While more DG capacity could be utilized to reduce the substation loading [3-9].

b) For reliability purposes if there should arise an occurrence of islanding, the DG size must be greater than double the required island load. The DG unit size can affect networks protection coordination schemes and devices as it affects the value of the short circuit current during fault.

Hence, as the DG size increases, the protection devices, fuses, re-closers and relays settings have to be readjusted and/or overhauled [1-2].

2.4 SUMMARY

In this chapter discusses the relevant issues and aims at providing a general definition for distributed power generation in competitive electricity markets. In general, DG can be defined as electric power generation within distribution networks or on the customer side of the network. In addition, the terms distributed resources, distributed capacity and distributed utility are discussed.

CHAPTER-3

INCORPORATION OF DG MODEL IN DISTRIBUTION NETWORK LOAD FLOWS

3.1 INTRODUCTION

The load flow of a power system gives the unfaltering state result through which different parameters of investment like currents, voltages, losses and so on can be figured. The load flow will be imperative for the investigation of distribution networks, to research the issues identified with planning, outline and the operation and control. A few provisions like ideal distributed generation placement in distribution networks and distribution automation networks, obliges rehashed load flow result. Numerous systems such Gauss-Seidel, Newton-Raphson are generally appeared for convey the load flow of transmission networks [1]. The utilization of these systems for distribution networks may not be worthwhile in light of the fact that they will be generally focused around the general meshed topology of a normal transmission networks although most distribution networks structure are likely in tree, radial or weakly meshed in nature. R/X ratio of distribution networks is high respect to transmission system, which cause the distribution networks to be badly molded for ordinary load flow techniques[1-2]. Some other inborn aspects of electric distribution networks are (i) radial or weakly meshed structure, (ii) unbalanced operation and unbalanced distributed loads, (iii) large number of nodes and branches, (iv) has wide range of resistance and reactance values and (v) distribution networks has multiphase operation.

The effectiveness of the optimization problem of distribution networks relies on upon the load flow algorithm on the grounds that load flow result need to run for ordinarily. Thusly, the load flow result of distribution networks ought to have ronodet and time proficient qualities. A technique which can discover the load flow result of radial distribution networks specifically by utilizing topological normal for distribution system [69-70] [72-74] is utilized. In this strategy, the plan of tedious Jacobian matrix or admittance matrix, which are needed in customary techniques, is stayed away from. This system is illustrated in a nutshell.

3.2 LOAD FLOW OF RADIAL DISTRIBUTION NETWORKS

A feeder brings power from substation to load points/nodes in radial distribution networks (RDN). Single or multiple radial feeders are used in this planning approach. Basically, the RDN total power losses can be minimized by minimizing the branch power flow or transported electrical power from transmission networks (i.e. some percentage of load are locally meeting by local DG). To determine the total power loss of the network or each feeder branch and the maximum voltage deviation are determined by performing load flow. The Forward/Backward Sweep Load Flow technique is used in this case. The impedance of a feeder branch is computed by the specified resistance and reactance of the conductors used in the branch construction. The Forward/Backward Sweep Load Flow method consist two steps (i) backward sweep and (ii) forward sweep.

Backward sweep: In this step, the load current of each node of a distribution network having N number of nodes is determined as:

$$\bar{I}_L(m) = \left\{\frac{P_L(m) - jQ_L(m)}{\bar{V}^*(m)}\right\} \qquad [\, m = 1,2,3 \ldots \ldots \ldots N] \tag{3.1}$$

where, $P_L(m)$ and $Q_L(m)$ represent the active and reactive power demand at node *m* and the overbar notation $(\bar{x})$ indicates the phasor quantities, such as $\bar{I}_L, \bar{V}^*$. Then, the current in each branch of the network is computed as:

$$\bar{I}(mn) = \bar{I}_L(n) + \sum_{m \in \Gamma} \bar{I}_L(m) \tag{3.2}$$

where, the set Γ consists of all nodes which are located beyond the node *n* [32].

Forward sweep**:** This step is used after the backward sweep so as to determine the voltage at each node of a distribution network as follows:

$$\bar{V}(n) = \bar{V}(m) - \bar{I}(mn)Z(mn) \tag{3.3}$$

where, nodes *n* and *m* represent the receiving and sending end nodes, respectively for the branch *mn* and $Z(mn)$ is the impedance of the branch.

In this work the estimation methodology utilized within the forward/backward load flow is based on (i) equivalent current injections (ECI), (ii) the node-injection to branch-current matrix (BIBC) and (ii) the branch-current to node-voltage matrix (BCBV). In this area, the advancement methodology will be depicted in subtle element. Load flow for distribution networks under balanced operating condition with constant power load model can be under remained through the accompanying focuses:

3.2.1 Equivalent Current Injection

The technique is based on the equivalent current injection of a node in distribution networks, the equivalent-current-injection model is more practical [69-70] [73]. For any node of distribution networks, the complex load S_i is expressed by

$$S_i = P_i + jQ_i \qquad i = 1, \ldots \ldots \ldots N_B \tag{3.4}$$

Now, the equivalent current injection is expressed as

$$I_i = I_i^r(V_i) + jI_i^i(V_i) = \left(\frac{P_i + jQ_i}{V_i}\right)^* \qquad i = 1, \ldots \ldots \ldots N_B \tag{3.5}$$

For the load flow solution equivalent current injection (ECI) at the *k-th* iteration at *i-th* node is computed as

$$I_i^k = I_i^r(V_i^k) + jI_i^i(V_i^k) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^* \tag{3.6}$$

3.2.2 Formation of BIBC Matrix

The power injections at every node might be transformed into the equivalent current injections using the eq. (3.6) and applying Kirchhoff's Current Law (KCL) at each and every node a set of comparisons could be composed. Now each and every branch currents of the network can be shaped as a function of the equivalent current injections (ECI) [69-70] [73]. As shown in Figure 3.1, the branch currents IB_5, IB_4, IB_3, IB_2 and IB_1 can be expressed as:

$$IB_5 = I_6 \tag{3.7}$$

$$IB_4 = I_5 \tag{3.8}$$

$$IB_3 = I_4 + I_5 \tag{3.9}$$

$$IB_2 = I_6 + I_3 + I_4 + I_5 \tag{3.10}$$

$$IB_1 = I_2 + I_3 + I_4 + I_5 + I_6 \tag{3.11}$$

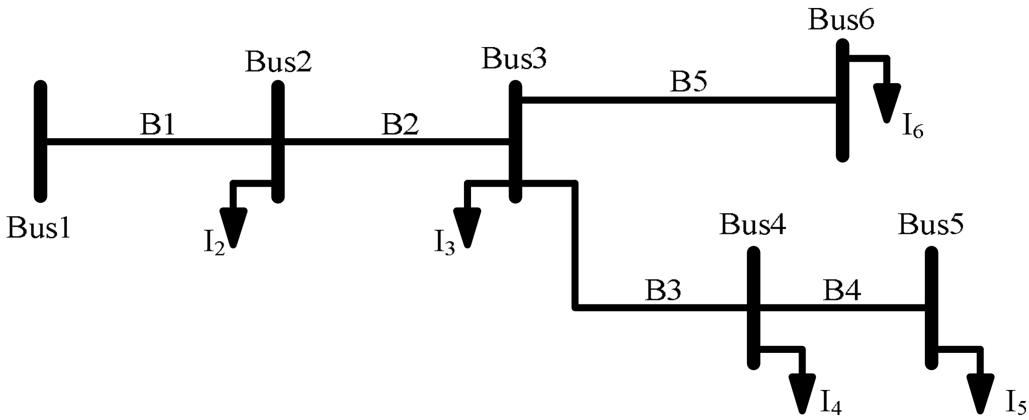


Figure 3.1. Simple distribution system

From the above equations () the BIBC matrix can be written as:

$$\begin{bmatrix} IB_1 \\ IB_2 \\ IB_3 \\ IB_4 \\ IB_5 \end{bmatrix} = \begin{bmatrix} 1\,1\,1\,1\,1 \\ 0\,1\,1\,1\,1 \\ 0\,0\,1\,1\,0 \\ 0\,0\,0\,1\,0 \\ 0\,0\,0\,0\,1 \end{bmatrix} \begin{bmatrix} I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \end{bmatrix} \tag{3.12}$$

The general form as of eq. (3.12) can be expressed as:

$$[IB] = [BIBC][I] \tag{3.13}$$

The detailing of BIBC matrix for distribution networks demonstrated in Figure 3.1 is given in eq. (3.13). For general network, the BIBC matrix might be shaped through the accompanying steps and the example is done by the help of Figure 3.1:

Step 1: Make an initial null BIBC matrix with a dimension of $(m \times (n-1))$. Where m and n are the number of branches and nodes available in the network.

Step 2: initially set i=1 and read the IB_i (i=1, 2, 3…m) branch data (i.e. sending end and receiving end node) from line-data matrix. If a line section IB_i is located between Node ‘x’ and Node ‘y’. Check, that the IB_i branch section of the network is belongs to the first node of the network or not. If it is, then make the *(y-1, y-1)-th* bit of BIBC matrix by ‘+1’. Increment ‘i’ by one or go to the step#3.

Step 3: If the in step#2 the IB_i branch section is not belongs to the first node of the network. Then copy the column segment of the *‘(x-1)-th’* node of BIBC matrix to the column segment of *‘(y-1)-th’* node and fill *(y-1, y-1)-th* bit of the BIBC matrix by ‘+1’. Increment ‘i’ by one and go to the step#2. This is explained in fig 3.2

Step 4: Repeat step#2 and step#3 until all the branches of the network included in to the BIBC matrix.

Step#1
$$\begin{bmatrix}0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}$$

i=1
$$\begin{bmatrix}1&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}$$
In step#2

i=2
$$\begin{bmatrix}1&1&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix} \rightarrow \begin{bmatrix}1&1&0&0&0\\0&1&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}$$
Copy 1st column — In step#3

i=3
$$\begin{bmatrix}1&1&1&0&0\\0&1&1&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix} \rightarrow \begin{bmatrix}1&1&1&0&0\\0&1&1&0&0\\0&0&1&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}$$
Copy 2nd column — In step#3

i=4
$$\begin{bmatrix}1&1&1&1&0\\0&1&1&1&0\\0&0&1&1&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix} \rightarrow \begin{bmatrix}1&1&1&1&0\\0&1&1&1&0\\0&0&1&1&0\\0&0&0&1&0\\0&0&0&0&0\end{bmatrix}$$
Copy 2nd column — In step#3

i=5
$$\begin{bmatrix}1&1&1&0&0\\0&1&1&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix} \rightarrow \begin{bmatrix}1&1&1&1&1\\0&1&1&1&1\\0&0&1&1&0\\0&0&0&1&0\\0&0&0&0&1\end{bmatrix}$$
Copy 2nd column — In step#3

Branch no	Sending node	Receiving node
1	1	2
2	2	3
3	3	4
4	4	5
5	3	6

Copied column — Updated column

Figure 3.2. The formation of BIBC matrix, the example is done by the help of Figure 3.1.

3.2.3 Formation of BCBV matrix

The Branch-Current to Node voltage (BCBV) matrix summarizes the relation between branch current and node voltages. The relations between the branch currents and node voltages can be obtained easily by applying Kirchhoff’s Voltage Law (KVL). As shown in Figure 3.1, the voltages of Node 2, 3, and 4 are expressed as:

$$V_2 = V_1 - IB_1 Z_{12} \tag{3.14}$$

$$V_3 = V_2 - IB_2 Z_{23} \tag{3.15}$$

$$V_4 = V_3 - IB_3 Z_{34} \tag{3.16}$$

Substituting equations (3.14) and (3.15) into eqn. (3.16), the voltage of Node 4 can be rewritten as:

$$Or, \quad V_4 = V_1 - IB_1Z_{12} - IB_2Z_{23} - IB_3Z_{34} \tag{3.17}$$

From equation it can be seen that the node voltage of the network can be expressed as a function of the branch currents, line parameters and main substation voltage. Similar approach can be employed for other nodes, and the Branch-Current to Node-Voltage (BCBV) matrix can be derived as:

$$\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix} = \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ Z_{12} & Z_{23} & 0 & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & 0 & 0 \\ Z_{12} & Z_{23} & Z_{34} & Z_{45} & 0 \\ Z_{12} & Z_{23} & 0 & 0 & Z_{56} \end{bmatrix} \begin{bmatrix} IB_1 \\ IB_2 \\ IB_3 \\ IB_4 \\ IB_5 \end{bmatrix} \tag{3.18}$$

The general form of eq. (3.18) can be expressed as:

$$Or, \ [\Delta V] = [BCBV][IB] \tag{3.19}$$

The formulation of BCBV matrix for distribution networks shown in Figure 3.1 is given eq. (3.18) and eq. (3.19). For universal network, the BCBV matrix can be formed through the subsequent steps:

Step 1: Make an initial null BVBC matrix with a dimension of $((n-1) \times m)$. Where m and n are the number of branches and nodes available in the network.

Step 2: initially set i=1 and read the IB_i (i=1, 2, 3…m) branch data (i.e. sending end and receiving end node) from line-data matrix. If a line section IB_i is located between Node ‘x’ and Node ‘y’. Check, that the IB_i branch section of the network is belongs to the first node of the network or not. If it is, then make the *(y-1, y-1)-th* bit of BVBC matrix by the corresponding branch impedance (Z_{xy}). Increment ‘i’ by one or go to the step#3.

Step 3: If the in step#2 the IB_i branch section is not belongs to the first node of the network. Then copy the row segment of the *‘(x-1)-th’* node of BVBC matrix to the row segment of *‘(y-1)-th’* node and fill *(y-1, y-1)-th* bit of the BVBC matrix by the corresponding branch impedance (Z_{xy}). Increment ‘i’ by one and go to the step#2. This is explained in Figure 3.2.

Step 4: Repeat step#2 and step#3 until all the branches of the network included in the BVBC matrix.

From Figure (3.2) and Figure (3.3), it can be seen that the algorithms for the both BIBC and BCBV matrices are virtually identical. Basic formation difference of BIBC matrix and BCBV matrix is that, in BIBC matrix *(x-1)-th* node column is copied to the column of the *(y-1)-th* node and fill with +1 in the *(x-1)-th* row and the *(y-1)-th* node column, while in BCBV matrix row of the *(x-1)-th* node is copied to the row of the *(y-1)-th* node and fill the line impedance (Z_{xy}) in the position of the *(y-1)-th* node row and the *i-th* column.

$$[\mathrm{BCBV}] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ 0 & Z_{23} & 0 & 0 & 0 \\ 0 & 0 & Z_{34} & 0 & 0 \\ 0 & 0 & 0 & Z_{45} & 0 \\ 0 & 0 & 0 & 0 & Z_{56} \end{bmatrix} \tag{3.20}$$

$$[\mathrm{BCBV}] = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}^T \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ 0 & Z_{23} & 0 & 0 & 0 \\ 0 & 0 & Z_{34} & 0 & 0 \\ 0 & 0 & 0 & Z_{45} & 0 \\ 0 & 0 & 0 & 0 & Z_{56} \end{bmatrix} \tag{3.21}$$

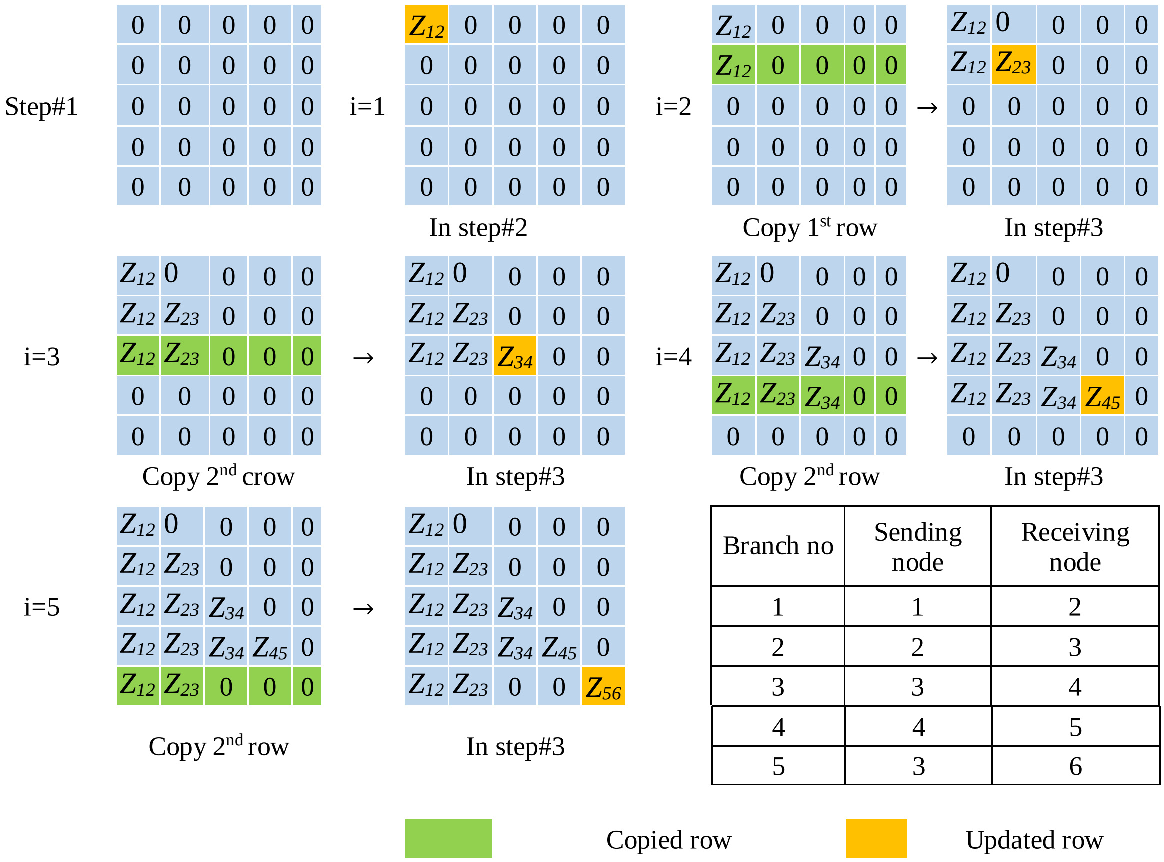
$$[\mathrm{BCBV}] = [\mathrm{BIBC}][\mathrm{ZD}] \tag{3.22}$$

$$\begin{bmatrix} V_1 \\ V_1 \\ V_1 \\ V_1 \\ V_1 \end{bmatrix} - \begin{bmatrix} V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Z_{12} & 0 & 0 & 0 & 0 \\ 0 & Z_{23} & 0 & 0 & 0 \\ 0 & 0 & Z_{34} & 0 & 0 \\ 0 & 0 & 0 & Z_{45} & 0 \\ 0 & 0 & 0 & 0 & Z_{56} \end{bmatrix} \begin{bmatrix} IB_1 \\ IB_2 \\ IB_3 \\ IB_4 \\ IB_5 \end{bmatrix} \tag{3.23}$$

The general form of eq. (3.23) can be expressed as:

$$[\Delta V] = [BCBV][ZD][IB] \tag{3.24}$$

$$[\Delta V] = [BIBC]^T[ZD][IB] \tag{3.25}$$



Branch no	Sending node	Receiving node
1	1	2
2	2	3
3	3	4
4	4	5
5	3	6

Figure 3.3. The formation of BVBC matrix, the example is done by the help of Figure 3.1.

3.2.4 Solution Methodology

The development of BIBC and BCBV matrices is clarified in section 3.2.2 and 3.2.3. These matrices investigate the topological structure of distribution networks. Basically the BIBC matrix is making an easy relation between the node current injections and branch currents. These relation give a simple solution for branch currents variation, which is occurs due to the variation at the current injection nodes, these can be obtained directly by using BIBC matrix. The BCBV matrix build an effective relations between the branch currents and node voltages. The concern variation of the node voltages is produced by the variant of the branch currents. These could be discovered specifically by utilizing the BCBV matrix. Joining eqs. (3.13) and (3.19), the relations between the node current injections and node voltages could be communicated as:

$$[\Delta V] = [BCBV].[BIBC].[I] \tag{3.26}$$

$$Now \qquad [BCBV] = [BIBC]^T.[ZD] \tag{3.27}$$

$$\therefore \qquad [\Delta V] = [BIBC]^T.[ZD].[BIBC].[I] \tag{3.28}$$

$$\therefore \qquad [DLF] = [BCBV][BIBC] \tag{3.29}$$

$$\therefore \qquad [DLF] = [BIBC]^T.[ZD].[BIBC] \tag{3.30}$$

$$Therefor \qquad [\Delta V] = [DLF].[I] \tag{3.31}$$

The iterative solution for the distribution system load flow can be obtained by solving eqs. (3.32) and (3.33) which are specified below:

$$I_i^k = I_i^r(V_i^k) + jI_i^i(V_i^k) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^* \tag{3.32}$$

$$[\Delta V^{k+1}] = [DLF].[I^k] \tag{3.33}$$

$$[V^{k+1}] = [V^0] + [\Delta V^{k+1}] \tag{3.33}$$

The new definition as illustrated uses just the DLF matrix to take care of load flow problem. Subsequently this strategy is extremely time efficient, which is suitable for on-line operation and optimization problem of distribution networks.

3.3 ALGORITHM FOR DISTRIBUTION NETWORKS LOAD FLOW

The algorithm steps for load flow solution of distribution networks is given below:

Step 1: Read the distribution networks line data and bus data.

Step 2: Calculate the each node current or node current injection matrix. The relationship can be expressed as –

$$[I] = \left[\frac{S}{V}\right]^* = \left[\frac{P - jQ}{V^*}\right]$$

Step 3: Calculate the BIBC matrix by using steps given in section 3.2.2.

Step 4: Evaluate the branch current by using BIBC matrix and current injection matrix (ECI). The relationship can be expressed as -

$$[IB] = [BIBC][I]$$

Step 5: Form the BCBV matrix by using steps given in section 3.2.3. The relationship therefore can be expressed as -

$$[\Delta V] = [BCBV][IB]$$

Step 6: Calculate the DLF matrix by using the eq. (3.30). The relationship will be -

$$[DLF] = [BCBV][BIBC]$$

$$[\Delta V] = [DLF][I]$$

Step 7: Set Iteration k = 0.

Step 8: Iteration k = k + 1.

Step 9: Update voltages by using eqs. (3.32), (3.33), (3.34), as –

$$I_i^k = I_i^r(V_i^k) + jI_i^i(V_i^k) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^*$$

$$[\Delta V^{k+1}] = [DLF].[I^k]$$

$$[V^{k+1}] = [V^0] + [\Delta V^{k+1}]$$

Step 10: If max $\big((|V(k+1)| - |V(k)|) > tolerance\big)$ go to step 6.

Step 11: Calculate branch currents, and losses from final node voltages.

Step 12: Display the node voltage magnitudes and angle, branch currents and losses.

Step 13: Stop

The above algorithm steps are shown in Flowchart given as Figure 3.4.

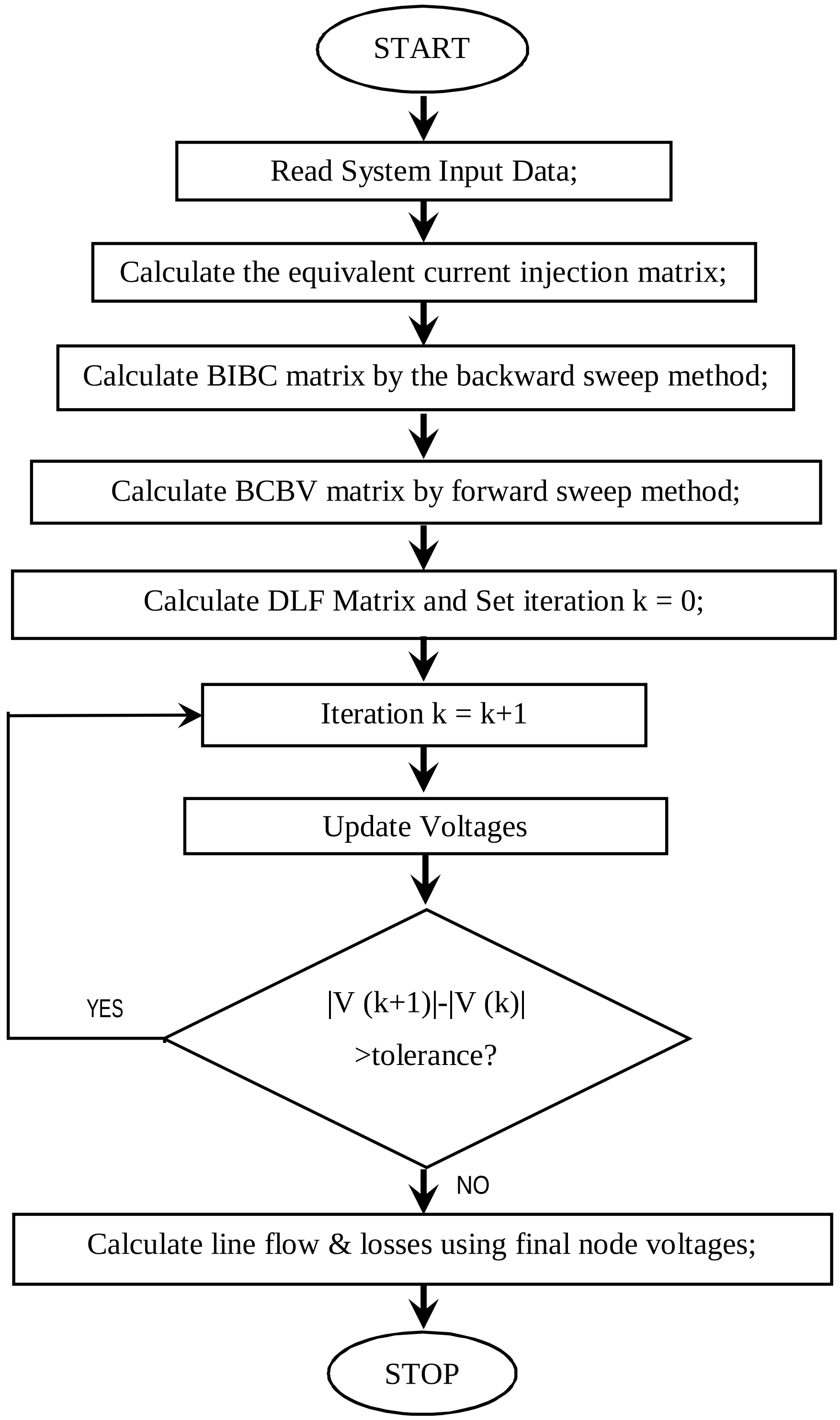


Figure 3.4. Flowchart for load flow solution for radial distribution networks.

3.4 INCORPORATION OF DG INTO LOAD FLOW

Assume that a single-source radial distribution networks with N_L branches and a DG is to be placed at node *i* and α be a set of branches connected between the source and node *i*. It is known that, the DG supplies active power $(P_{G_i}^{DG})$ to the systems, but in case of reactive power $(Q_{G_i}^{DG})$ it is depend upon the source of DG, either it is supplies to the systems or consume from the systems. Due to this active and reactive power an active current $(I_{DG_i}^{r})$ and reactive current $(I_{DG_i}^{i})$ flows through the system, and it changes the active and reactive component of current of branch set α. The current of other branches (∉=α) are unaffected by the DG.

Total Apparent Power at i^{th} node:

$$S = S_{D\_i} = \sum P_{D\_i} + jQ_{D\_i} \qquad i = 1, \ldots N_B \tag{3.34}$$

Current at i^{th} node:

$$I_D = I_{D\_i}^{without\_DG} = \left(\frac{S_{D\_i}}{V_i}\right)^* \tag{3.35}$$

To incorporate the DG model, the active and reactive power demand at ***i-th*** node at which a DG unit is placed, is modified by:

$$P_{D\_i}^{with\_DG} = P_{D\_i}^{without\_DG} - P_{G\_i}^{DG} \tag{3.36}$$

$$Q_{D\_i}^{with\_DG} = Q_{D\_i}^{without\_DG} \mp Q_{G\_i}^{DG} \tag{3.37}$$

DG power at i^{th} node:

$$S_{DG\_i} = \sum P_{G\_i}^{DG} \pm jQ_{G\_i}^{DG} \qquad i = 1, 2, 3, \ldots N_B \tag{3.38}$$

Total new apparent power at i^{th} node:

$$S = S_{D\_i} - S_{DG\_i} \tag{3.39}$$

So, new current at i^{th} node:

$$I_D = I_{D\_i}^{with\_DG} = \left(\frac{S_{D\_i} - S_{DG\_i}}{V}\right)^* \tag{3.40}$$

Now the updated network power can be expressed in matrix form

$$[S] = [S_{D_i}] - [S_{DG_i}] \tag{3.41}$$

3.5 INCORPORATION OF ON-LINE LOAD TAP CHANGER (OLTC) INTO LOAD FLOW

OLTC is generally placed in the line of a distribution system. Let, a OLTC is placed in a line and it have the off-nominal tap ratio of *(1:a)* with a series admittance of Y_{tI} as shown in Fig.4. We know that there is a direct relations between [*ZD*] and [*B*]. If an OLTC is placed in a line then the transformer can be represented by a series admittance (Y_{tI}) in per unit as per the π model representation of OLTC [69-70] [73]. The off-nominal tap ratio of OLTC, per unit admittance of both side of the transformer is different, and it force to change the admittance to include the effect of off-nominal ratio. It's have a direct effect of the line current, for modification in the line admittance, line current relation need to be modified.

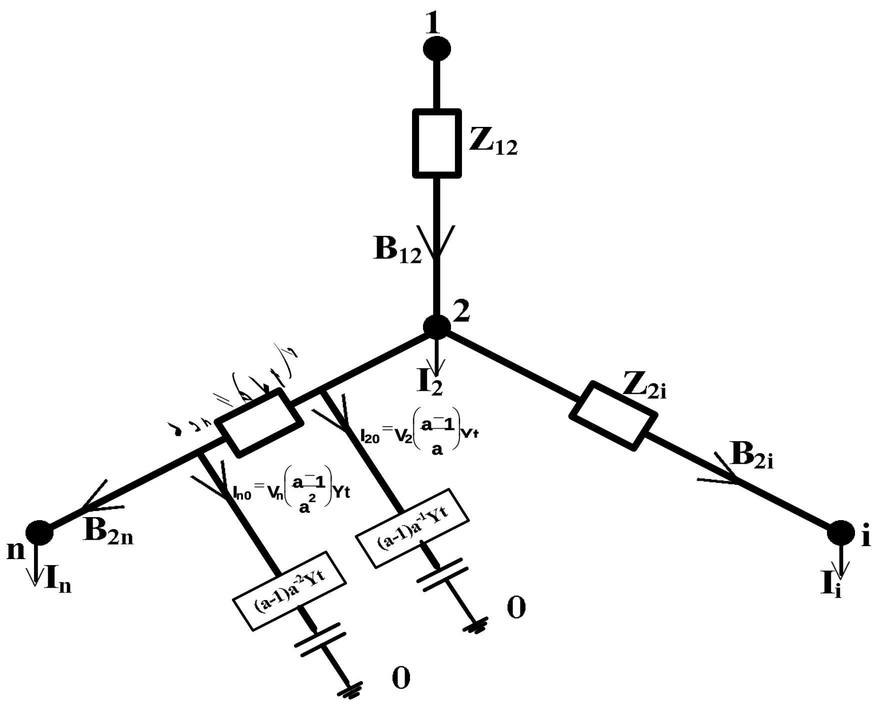


Figure 3.5. Network with off-nominal tap changing transformer.

The modified impedance matrix including the per unit series impedance Z_{2nI} of OLTC with the line impedance

$$[ZD] = \begin{bmatrix} Z_{12I} + 0 & 0 & 0 \\ 0 & (Z_{2iI} + 0) & 0 \\ 0 & 0 & (Z_{2nI} + Z_{2tI})/a \end{bmatrix} \tag{3.42}$$

In Figure 3.5. I_{20I} *and* I_{n0I} are non-tap to tap side currents are diverging from nodes *i* and *n* respectively. The modified equivalent current injection matrix including the off-nominal ratio is

$$[B] = [BIBC]\begin{bmatrix} I_{2I} - I_{20I} \\ I_{tI} \ -0 \\ I_{nI} - I_{n0I} \end{bmatrix} = [BIBC]\begin{bmatrix} I_{2I} - \left(\frac{a-1}{a}\right) Y_{tI} V_{2I} \\ I_{iI} \\ I_{nI} - \left(\frac{1-a}{a^2}\right) V_{tI} V_{nI} \end{bmatrix} \tag{3.43}$$

3.6 INCORPORATION OF CAPACITOR BANK INTO LOAD FLOW

Assume that a single-source radial distribution networks with N_B branches and a capacitor bank is to be placed at node *i*. The capacitor bank produces reactive power $(Q_{G\_i}^{CB})$ due to this a reactive current $(I_{CB_i}^{i})$ flow through the radial network branches which changes the reactive component of current of branch. To incorporate the capacitor bank model, the reactive power demand at *i-th* node at which a capacitor bank unit is placed, is modified by:

$$Q_{D\_i}^{with\_CB} = Q_{D\_i}^{without\_CB} - Q_{G\_i}^{CB} \tag{3.44}$$

$$[S] = [S_{D_i}] - [S_{CB_i}] \tag{3.45}$$

3.7 ALGORITHM FOR DISTRIBUTION NETWORKS LOAD FLOW WITH DG

The algorithm steps for load flow solution of distribution networks is given below:

Step 1: Read the distribution networks line data and bus data.

Step 2: Calculate DG power and capacitor bank power for each nodes and update the system bus data.

Step 3: Calculate the total power demand with DG or capacitor bank or with both by the help of eq. (3.41) (3.45). The relationship can be expressed as –

$$[S] = [S_{D_i}] - [S_{DG_i}] - [S_{CBi}]$$

Step 4: Calculate the each node current or node current injection matrix. The relationship can be expressed as –

$$[I] = \left[\frac{S}{V}\right]^* = \left[\frac{P - jQ}{V^*}\right]$$

Step 5: Calculate the modified impedance matrix and modified current injection matrix for tap changer by the help of eq. (3.42) (3.43).

Step 6: Calculate the BIBC matrix by using steps given in section 3.2.2.

Step 7: Evaluate the branch current by using BIBC matrix and current injection matrix (ECI). The relationship can be expressed as -

$[IB] = [BIBC][I]$

Step 8: Form the BCBV matrix by using steps given in section 3.2.3. The relationship therefore can be expressed as -

$[\Delta V] = [BCBV][IB]$

Step 9: Calculate the DLF matrix by using the eq. (3.30). The relationship will be -

$[DLF] = [BCBV][BIBC]$

$[\Delta V] = [DLF][I]$

Step 10: Set Iteration k = 0.

Step 11: Iteration k = k + 1.

Step 12: Update voltages by using eqs. (3.32), (3.33), (3.34), as –

$$I_i^k = I_i^r(V_i^k) + jI_i^i(V_i^k) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^*$$

$[\Delta V^{k+1}] = [DLF].[I^k]$

$[V^{k+1}] = [V^0] + [\Delta V^{k+1}]$

Step 13: If max $\left((|V(k+1)| - |V(k)|) > tolerance\right)$ go to step 6.

Step 14: Calculate branch currents, and losses from final node voltages.

Step 15: Display the node voltage magnitudes and angle, branch currents and losses.

Step 16: Stop

3.8 TEST SYSTEMS

The proposed technique is applied on two different system to validate the proposed scheme.

System#1: Standard IEEE 69-node Reliability Test System (RTS) [24] [35]. It have a single substation system with voltage magnitude of 1 p.u. and all other nodes are load node. From the system data it had been found that the load is varying highly (active power is varying from 0 to 1244kW, and reactive power is varying from 0 to 888kVAR). The system base MVA and base kVA are 10MVA and 11kV respectively with one slack node.

System#2: An 11kV Practical Distribution Network from southern India grid. It have total 52 nodes with 3 main feeders [34] and one main substation with a voltage magnitude of 1 p.u. The system base MVA and base kVA are 1MVA and 11kV respectively with one slack node.

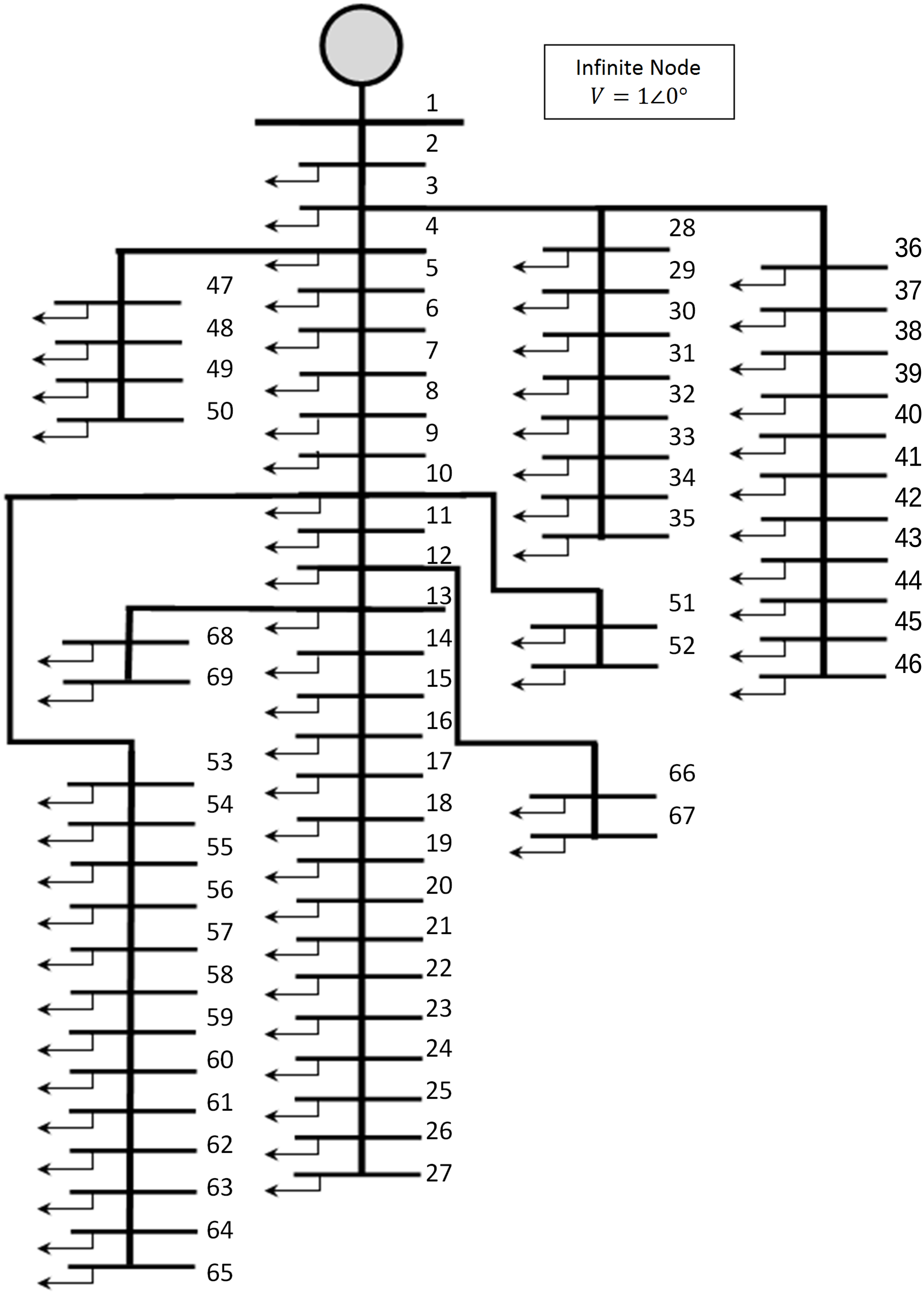


Figure 3.6. System #1, 69-node radial distribution networks

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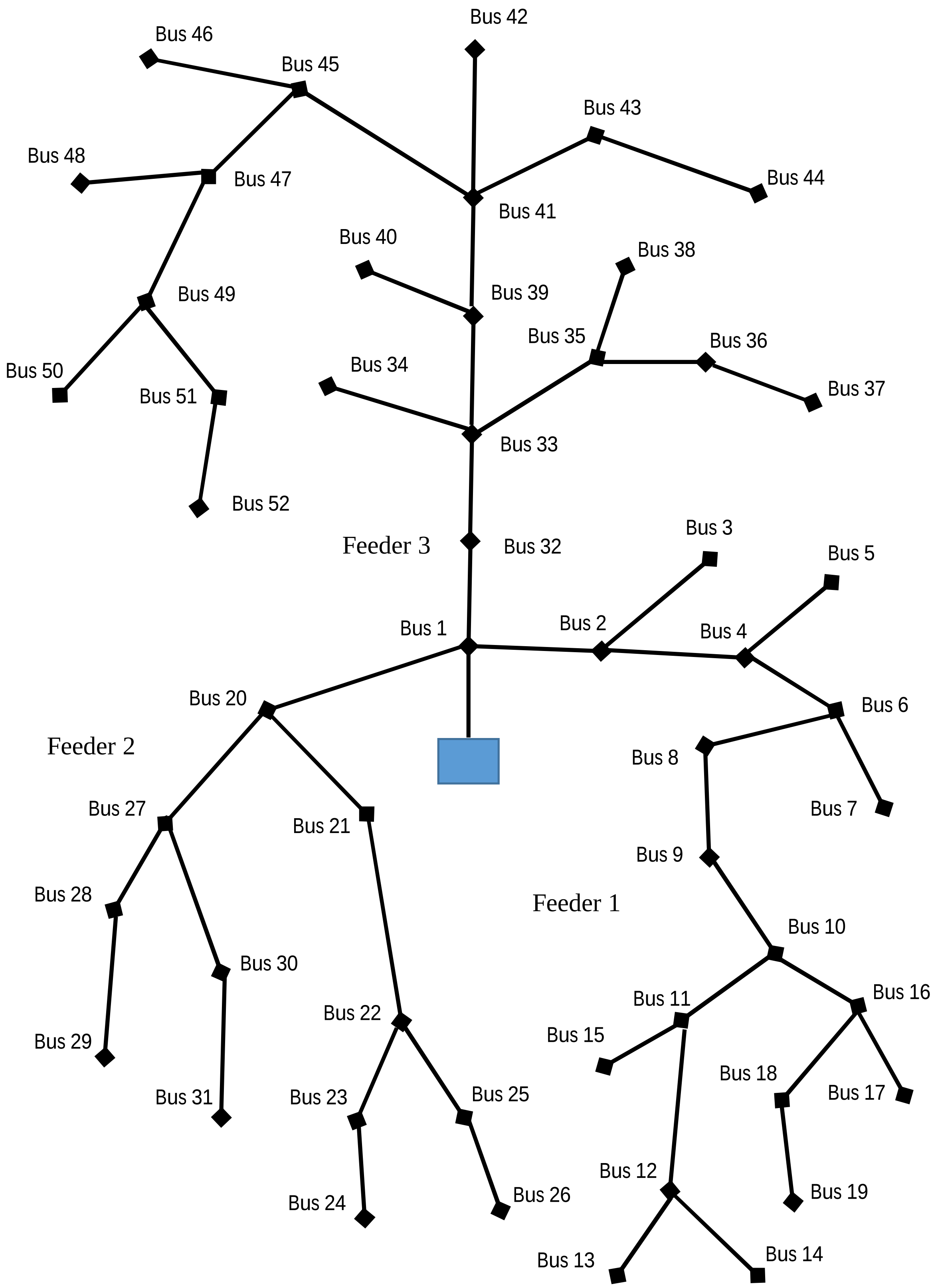


Figure 3.7. System #2, 52-node radial distribution networks

3.9 LOAD FLOW SOLUTION FOR BASE CASE

System #1: The total load of the networks is 4.660MW (3802.19 kW active power and 2694.6kVAR reactive power) and the slack node is delivering 4.902MW power. The distribution loss in the networks is 0.247 MW. The power loss due to active component of current is 224.995 kW and power loss due to reactive component of the current is 102.198 kVAR. All node voltages are within 0.90919 - 1p.u. Also the minimum voltage is 0.90919 p.u. is bearing the 65th number node of the system and the maximum branch current 0.49031p.u is bearing by the branch 1.The MATLAB® simulation result are shown in Figure 3.8 and Figure 3.9. The load flow study is carried out with an accuracy level of 10^-9, and maximum iteration of 300. The convergence of load flow with the accuracy level occur at 9 iteration. The Table 3.1 contains the node voltage magnitudes, branch current magnitudes, and the angle in radian of the converged load flow solutions. The results shows that, at the peak load condition system performance is not so poor. The system have a poor voltage profile at node 57 to node 65 due to the system hugely loaded at 61 node. While some of the node have no load.

System#2: The total load of the networks is 4.648 MW (4184 kW active power and 2025 kVAR reactive power) and the slack node is delivering 5.613 MW power. The distribution loss in the networks is 0.9658 MW. The power loss due to active component of current is 887.181 kW and power loss due to reactive component of the current is 381.694 kVAR. All node voltages are within 0.68442 - 1p.u. also the minimum voltage of 0.68442 p.u. is occurs at the 50th node and the maximum branch current of 2.4382 p.u flows through the 31th branch. The MATLAB® simulation result are shown in Figure 3.10 and Figure 3.11. In this case also the load flow study is carried out with an accuracy level of 10^-9, and maximum iteration of 300. The convergence of load flow with the accuracy level also occur at 9 iteration. The Table 3.2 contains the node voltage magnitudes, branch current magnitudes, and the angle in radian of the converged load flow solutions. The results shows that, at the peak load condition system performance is very poor. The system have a poor voltage profile at most of the nodes, basically at 5 to 19 and 32 to 52 nodes.

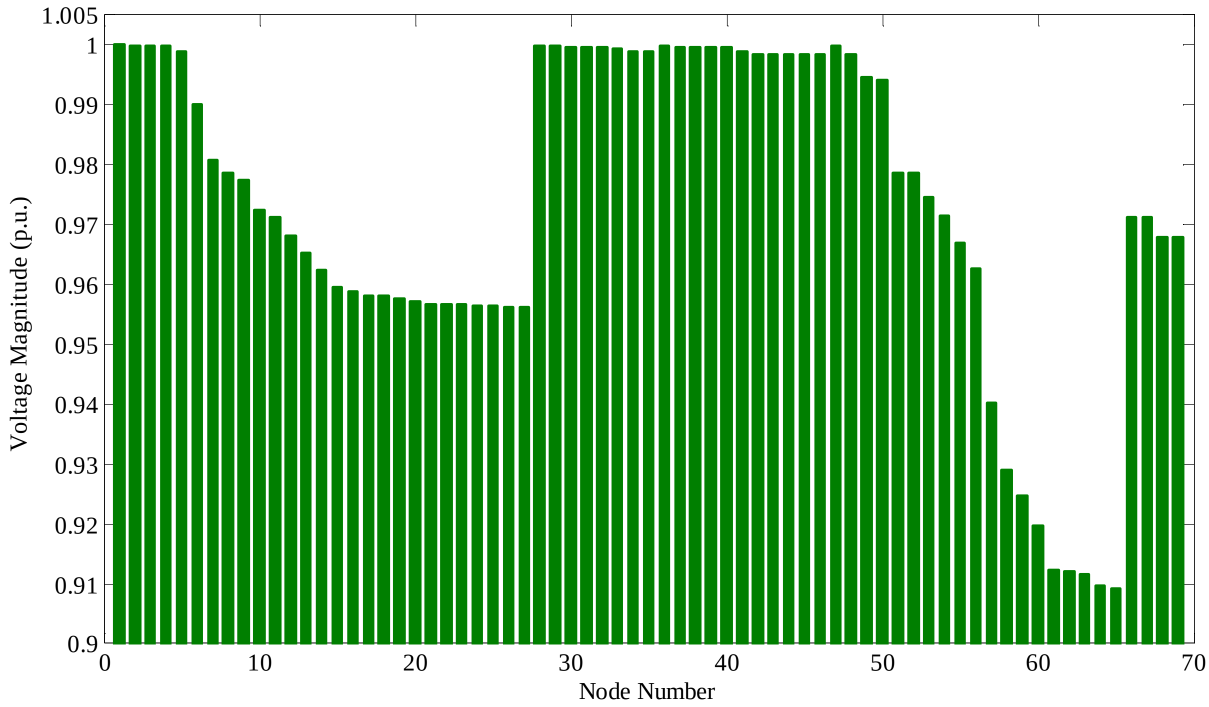


Figure 3.8. Base case node voltage magnitudes of system#1

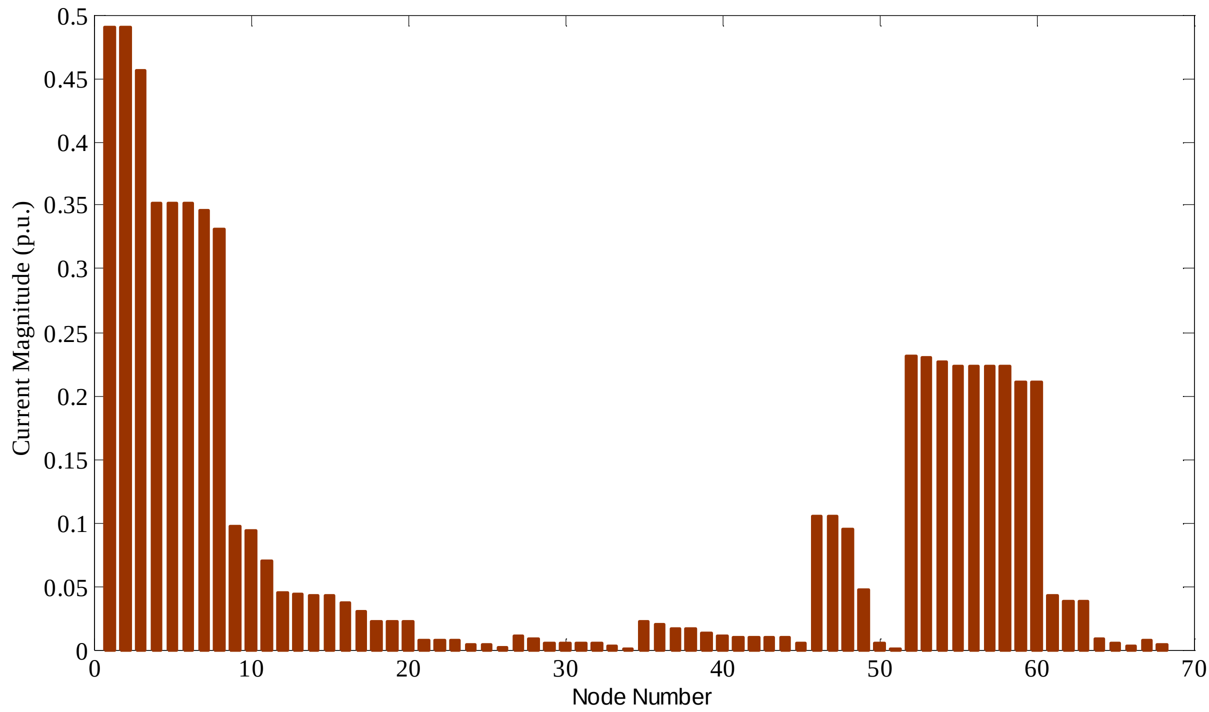


Figure 3.9. Base case branch current magnitudes of system#1

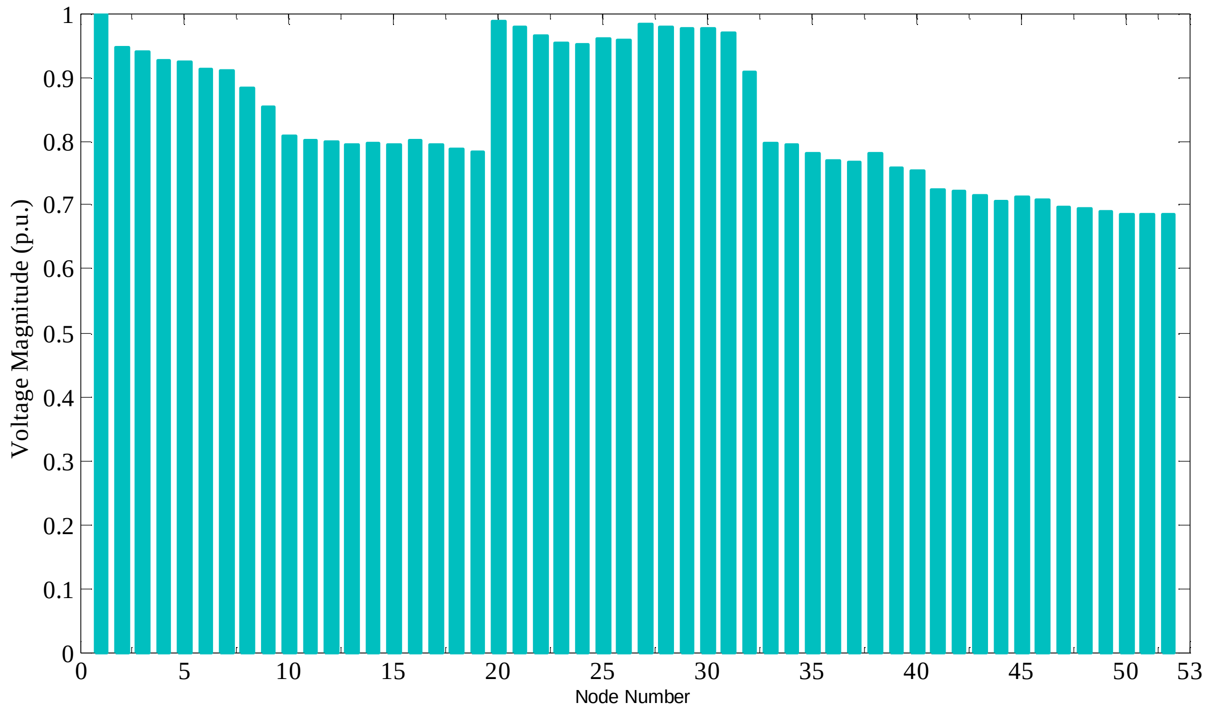


Figure 3.10. Base case node voltage magnitudes of system#2

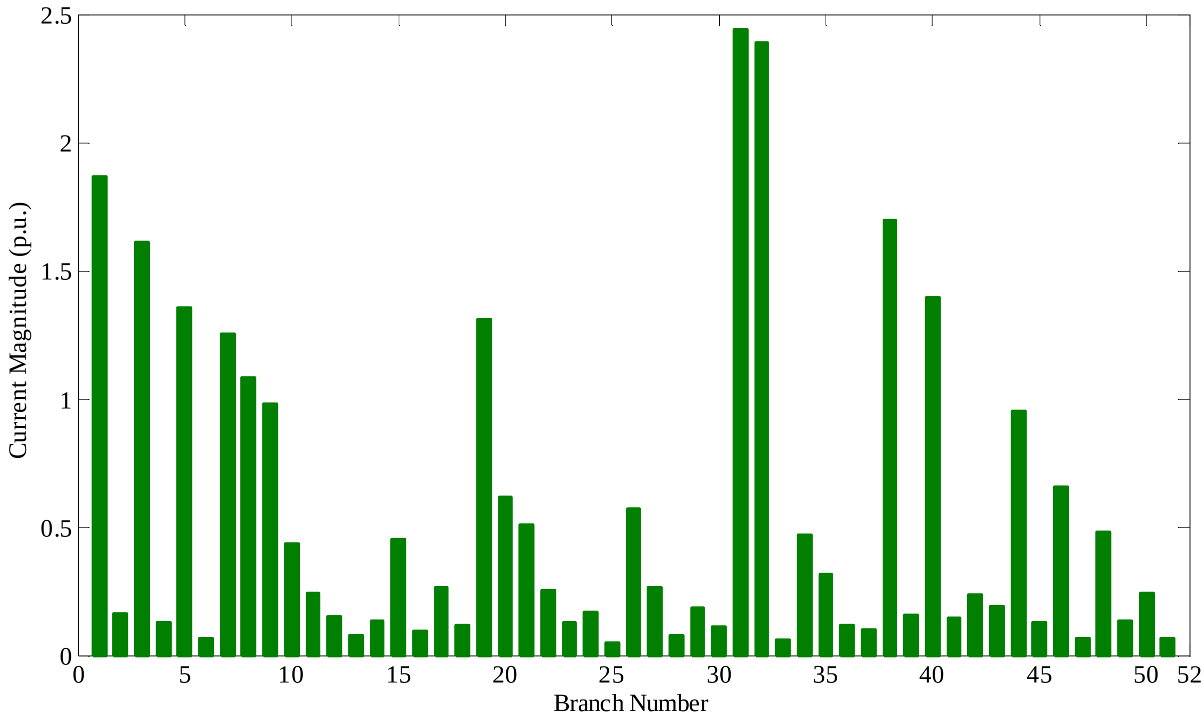


Figure 3.11. Base case branch current magnitudes of system#2

Table 3.1. Base case converged flow solution for system #1.

Node/ Branch	Voltage (p.u)	Angle (radian)	Current (p.u)
1	1	0	0.49031029
2	0.9999665	-2.14E-05	0.49031029
3	0.9999330	-4.29E-05	0.45644465
4	0.9998395	-0.000103	0.35169363
5	0.9990203	-0.000323	0.35169363
6	0.9900848	0.0008609	0.35135134
7	0.9807910	0.0021143	0.34622390
8	0.9785749	0.0024147	0.33127331
9	0.9774414	0.0025687	0.09670386
10	0.9724411	0.0040490	0.09322422
11	0.9713158	0.0043418	0.07028809
12	0.9681542	0.0052642	0.04476029
13	0.9652284	0.0060756	0.04375473
14	0.9623291	0.0068821	0.04274612
15	0.9594589	0.0076840	0.04274612
16	0.9589256	0.0078334	0.03706268
17	0.9580450	0.0080804	0.02982539
18	0.9580360	0.0080829	0.02259646
19	0.9575710	0.0082318	0.02259646
20	0.9572720	0.0083276	0.02247500
21	0.9567898	0.0084825	0.00785879
22	0.9567829	0.0084847	0.00719537
23	0.9567110	0.0085080	0.00719537
24	0.9565546	0.0085588	0.00359816
25	0.9563820	0.0086085	0.00359816
26	0.9563123	0.0086311	0.00179910
27	0.9562927	0.0086375	0.01124029
28	0.9999261	-4.72E-05	0.00804325
29	0.9998544	-9.26E-05	0.00484600
30	0.9997333	-5.55E-05	0.00484600
31	0.9997119	-4.90E-05	0.00484600
32	0.9996050	-1.62E-05	0.00484600
33	0.9993488	6.10E-05	0.00312443
34	0.9990133	0.0001632	0.00072187
35	0.9989459	0.0001818	0.02262620
36	0.999919	-5.18E-05	0.019432
37	0.999747	-0.00016	0.016238
38	0.999589	-0.00021	0.016238
39	0.999543	-0.00022	0.013296
40	0.999541	-0.00022	0.010354
41	0.998843	-0.00041	0.010198
42	0.998551	-0.00049	0.010198
43	0.998512	-0.0005	0.009459
44	0.998504	-0.0005	0.009459
45	0.998405	-0.00054	0.00473
46	0.998405	-0.00054	0.104769
47	0.999789	-0.00013	0.104769
48	0.998543	-0.00092	0.095048
49	0.994699	-0.00334	0.047537
50	0.994154	-0.00369	0.005509
51	0.978539	0.002420	0.000460
52	0.978530	0.002423	0.230766
53	0.974655	0.002951	0.230194
54	0.971412	0.003398	0.226847
55	0.966939	0.004019	0.223794
56	0.962570	0.004630	0.223794
57	0.940096	0.011551	0.223794
58	0.929036	0.015086	0.223794
59	0.924759	0.016500	0.210469
60	0.919734	0.018324	0.210469
61	0.912337	0.019529	0.042940
62	0.912047	0.019576	0.038620
63	0.911660	0.019640	0.038620
64	0.909759	0.019952	0.007966
65	0.909185	0.020045	0.004572
66	0.971259	0.004362	0.002286
67	0.971258	0.004362	0.007111
68	0.967824	0.005370	0.003555
69	0.967823	0.005370	

Table 3.2. Base case converged flow solution for system #2.

Node/ Branch	Voltage (p.u)	Angle (radian)	Current (p.u)	Node/ Branch	Voltage (p.u)	Angle (radian)	Current (p.u)
1	1	0	1.866065	27	0.982427	0.000785	0.261515
2	0.947626	0.002020	0.159368	28	0.978758	0.000960	0.077368
3	0.940172	0.002354	1.611831	29	0.976950	0.001044	0.186260
4	0.925007	0.002949	0.129840	30	0.975459	0.001104	0.108774
5	0.923185	0.003033	1.352408	31	0.970372	0.001337	2.437959
6	0.912355	0.003480	0.065779	32	0.908758	0.003349	2.387765
7	0.911124	0.003537	1.253784	33	0.797069	0.008460	0.057384
8	0.883032	0.004758	1.084104	34	0.794923	0.008588	0.468122
9	0.852608	0.006163	0.978664	35	0.781747	0.009387	0.312865
10	0.806836	0.008465	0.432591	36	0.770045	0.010133	0.117731
11	0.800766	0.008777	0.244147	37	0.767294	0.010321	0.096907
12	0.798482	0.008895	0.151022	38	0.779935	0.009492	1.693390
13	0.793703	0.009152	0.075291	39	0.757467	0.010512	0.158861
14	0.796017	0.009026	0.131326	40	0.754495	0.010679	1.395190
15	0.793568	0.009142	0.454050	41	0.724840	0.012352	0.146440
16	0.800466	0.008826	0.093921	42	0.720731	0.012605	0.233840
17	0.795197	0.009164	0.266830	43	0.714998	0.012941	0.191932
18	0.787986	0.009486	0.114713	44	0.706022	0.013496	0.951980
19	0.783694	0.009717	1.309082	45	0.711483	0.013142	0.127090
20	0.987756	0.000542	0.617945	46	0.707323	0.013390	0.656427
21	0.979087	0.000932	0.511059	47	0.696134	0.014092	0.065612
22	0.964746	0.001579	0.251957	48	0.695214	0.014155	0.482247
23	0.952963	0.002097	0.126174	49	0.689368	0.014516	0.131335
24	0.950012	0.002229	0.165920	50	0.684454	0.014819	0.241278
25	0.960092	0.001816	0.047602	51	0.685983	0.014732	0.066555
26	0.958311	0.001904	0.569785	52	0.685361	0.014775	

3.10 SUMMARY

In this chapter, a simple distribution system load flow approaches has been formulated. The Bus Injection to Branch Current (BIBC) matrix and Branch Current to Node voltage (BCBV) matrix are the main part of this approaches. This two matrix make the relation between the current injections to branch current and branch current to node voltage. The matrix formation makes the load flow calculation very easy. The incorporation of DG, capacitor bank and OLTTC into the load flow is much simple due to these calculation is basically based on matrix addition, subtraction or multiplication. Also the satisfactory result is obtained from the load flow approaches which is conducted on two different radial distribution systems. With the definition of this load flow of radial distribution networks, the highly required foundation has been ready to work in the area of distributed generator allocation problem in radial distribution networks.

CHAPTER-4

OPTIMAL DG ALLOCATION USING GENETIC ALGORITHM

4.1 INTRODUCTION

Optimization is a process by which we try to find out the best solution from set of available alternative. In DG allocation problem, DG locations and sizes must be optimize in such a way that it give most economical, efficient, technically sound distribution system. In general distribution system have many nodes and it is very hard to find out the optimal DG location and size by hand. There are numerous optimization approaches used in the literature. In most of the current works, population based evolutionary algorithms are used as optimization approaches (i.e. particle swarm optimization (PSO) [26-29], evolutionary programming [25], genetic algorithm (GA) [20-25], etc.). In the project work genetic algorithm is used as the solution strategy.

4.2 GENETIC ALGORITHM

Genetic Algorithms (GAs) are versatile exploratory hunt processes focused around the evolutionary ideas of characteristic choice and genetics. A genetic algorithm is a heuristically guided random search technique that concurrently evaluates thousands of postulated solutions. Biased random selection and mixing of the evaluated searches is then carried out in order to progress towards better solutions. The coding and manipulation of search data is based upon the operation of genetic DNA and the selection process is derived from Darwin's survival of the fittest'. Search data are usually coded as binary strings called chromosomes, which collectively form populations. Evaluation is carried out over the whole population and involves the application of, often complex 'fitness' functions to the string of values (genes) within each chromosome. Typically, mixing involves recombining the data that are held in two chromosomes that are selected from the whole population.

Evolutionary computing was introduced in the 1960s by I. Rechenberg in his work "Evolution strategies". His idea was then developed by other researchers. Genetic Algorithms (GAs) were invented by John Holland at the University of Michigan. This lead to Holland's book "Adaptation in Natural and Artificial Networks" published in 1975. The goals of their research have been twofold: (1) to abstract and rigorously explain the adaptive processes of natural networks and (2) to design artificial networks software that retains the important mechanisms of natural networks. The central theme of research on genetic algorithms has been ronodetness, the balance between efficiency and efficacy necessary for survival in many different environments. In 1992 John Koza has used genetic algorithm to evolve programs to perform certain tasks. He called this method "Genetic Programming" (GP).

4.2.1 GAs vs Conventional Algorithms

Genetic Algorithms are different from normal optimization and search methods in four ways:

1. GAs work with coding of the parameter set, not the parameters themselves.
2. GAs search from a population of points, not a single point.
3. GAs use payoff (objective function) information, not derivatives or other auxiliary knowledge.
4. GAs use probabilistic transition rules, not deterministic rules.

4.2.2 Genetic Algorithm Description

The genetic algorithm is a search algorithm that iteratively transforms a set (called a population) of mathematical objects (typically fixed-length binary character strings), each with an associated fitness value, into a new population of offspring objects using the Darwinian principle of natural selection and using operations such as crossover (sexual recombination) and mutation[75].

Algorithm begins with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions which are then selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. This is repeated until some condition is satisfied. The space of all feasible solutions (the set of solutions among which the desired solution resides) is called search space (also state space). Each point in the search space represents one possible solution. Each possible solution can be "marked" by its value (or fitness) for the problem. With GA we look for the best solution among a number of possible solutions. The problem is that the search can be very complicated. One may not know where to look for a solution or where to start. There are many methods one can use for finding a suitable solution, but these methods do not necessarily provide the best solution.

A simple genetic algorithm that yields good results in many practical problems is composed of three operators:

Reproduction: This operator is an artificial version of natural selection based on Darwinian survival of the fittest among string creatures. Reproduction operator can be implemented in algorithmic form in a number of ways.

Crossover: It occurs after reproduction or selection. It creates two new population or strings from two existing ones by genetically recombining randomly chosen parts formed by randomly chosen crossover point.

Mutation: It is the occasional random alteration of the value of a string position. Mutation creates a new string by altering value of existing string.

<u>Fitness function</u>: A typical genetic algorithm requires two things to be defined: (1) a genetic representation of solutions, (2) a fitness function to evaluate them. The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. Once we had the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, then improve it through repetitive application of mutation, crossover, and selection operators.

4.2.3 Parameters of GA

There are two basic parameters of GA - crossover probability and mutation probability. Other parameters include population size etc.

Crossover probability is how often crossover will be performed. If there is no crossover, offspring are exact copies of parents. If there is crossover, offspring are made from parts of both parent's chromosome. If crossover probability is 100%, then all offspring are made by crossover. If it is 0%, whole new generation is made from exact copies of chromosomes from old population. Crossover is made in hope that new chromosomes will contain good parts of old chromosomes and therefore the new chromosomes will be better.

Mutation probability is how often parts of chromosome will be mutated. If there is no mutation, offspring are generated immediately after crossover (or directly copied) without any change. If mutation is performed, one or more parts of a chromosome are changed. If mutation probability is 100%, whole chromosome is changed, if it is 0%, nothing is changed. Mutation generally prevents the GA from falling into local extremes. Mutation should not occur very often, because then GA will in fact change to random search.

Population size is how many chromosomes are in population (in one generation). If there are too few chromosomes, GA have few possibilities to perform crossover and only a small part of search space is explored. On the other hand, if there are too many chromosomes, GA slows down.

4.2.4 Algorithm of Basic GA

Step 1: Generate random population of η_{pop} chromosomes.

Step 2: Evaluate the objective function $\psi(x)$ and fitness $f(\psi)$ of each chromosome x in the population

Step 3: Select the pairs of chromosome as parents from the population with giving a priority that the better fitness parents will get highest chance to be selected in the matting pool.

Step 4: According to the matting pool parents are crossed over with a crossover probability and generate the offspring.

Step 5: Now the crossed offspring are mutated with a mutation probability where the offspring locus are change slightly.

Step 6: Consider the mutate offspring as a new population and use it for the next generation.

Step 7: If the solution satisfied the end condition, then stop, and display the optmial solution.

Step 8: Go to step 2

The standard procedure of GA is shown in flowchart as shown in Figure 4.1.

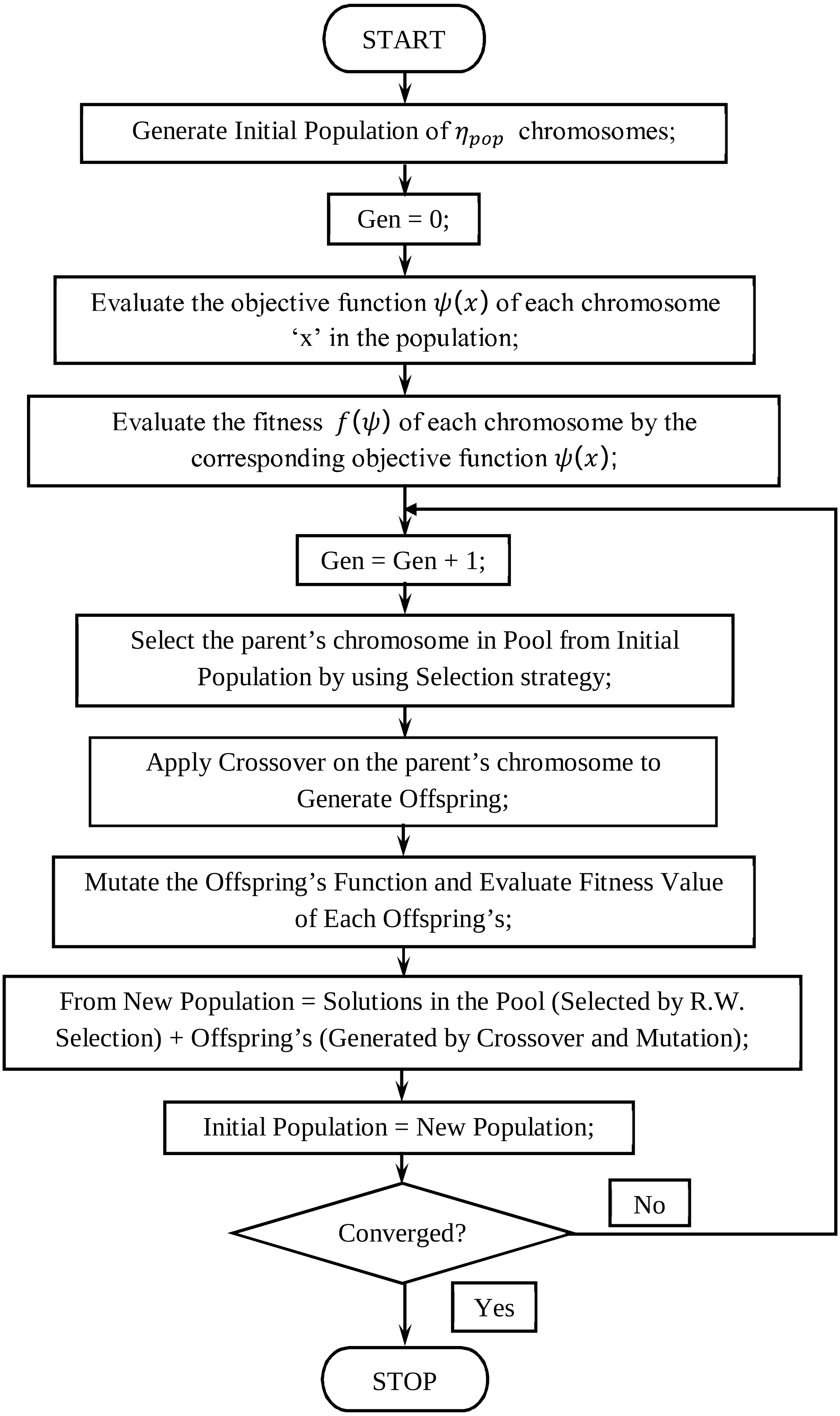


Figure 4.1. Flowchart for basic GA algorithms

4.2.5 Applications of GA

Problems which give off an impression of being especially suitable for result by hereditary calculations (genetic algorithms) incorporate timetabling and scheduling issues, and numerous planning programming bundles are focused around GAs. GAs have likewise been connected to engineering. Genetic algorithms are regularly connected as a methodology to take care of global optimization problems. When in doubt of thumb genetic algorithms may be valuable in issue areas that have a complex fitness landscape as mixing, i.e., mutation in consolidation with crossover, is intended to move the populace far from local optima that a conventional 'hill climbing' algorithm may get stuck in. Since GAs are mainly used in optimization and give outstanding performance, GAs are treated as function optimiser. But there are many other ways to view genetic algorithms in different areas such as:

- GAs as problem solvers
- GAs as challenging technical puzzle
- GAs as basis for competent machine learning
- GAs as computational model of innovation and creativity
- GAs as computational model of other innovating networks
- GAs as guiding philosophy

Genetic algorithms have been used for difficult problems (such as NP-hard problems), for machine learning and also for evolving simple programs. They have been also used for some art, for evolving pictures and music. Some of the applications of GAs are:

- Nonlinear dynamical networks - predicting, data analysis
- Designing neural networks, both architecture and weights
- Robot trajectory
- Evolving LISP programs (genetic programming)
- Strategy planning
- Finding shape of protein molecules
- Signal Processing
- TSP and sequence scheduling

4.3 DG ALLOCATION OPTIMIZATION OBJECTIVE FUNCTION

In every optimization process must have an objective function on the basis of that the optimization will continue. In general, objective functions are two type, (i) single objective and (ii) multi objective. In this distribution system planning problem both the single-objective and multi-objective optimization problem are consider with the continuous planning decision variables. The main objective is to determine an economical yet reliable network with better technical features, such as lower power loss, better node voltage profile, and better branch current/thermal limit ratio while maximizing DG power (P_{DG}) in order to reduce the stress of excessive active and reactive power demand from transmission networks. Thus, two objective functions are formulated: minimization of (i) the total power loss (P_{loss}) of the distribution network and (ii) maximum node voltage deviation (V_{dev}) ratio. Optimization of (i) yields an economical and high efficient network and optimization of (ii) results in a reliable network with better technical features.

Single-objective optimization: In single objective optimization only the power loss of the RDS has been considered. The objective function mathematically formulated as

(i) Min $\psi(\Upsilon_p) = \left(\sum_i^{N_L} P_{loss}^{with\_DG}\right)$ (4.1)

(ii) Min $\psi(\Upsilon_p) = \left(\frac{\sum_i^{N_L} P_{loss}^{with\_DG}}{\sum_i^{N_L} P_{loss}^{without\_DG}}\right)$ (4.2)

Multi-objective optimization: In case of multi-objective optimization both minimization of (i) the total power loss (P_{loss}) of the distribution network and (ii) maximum node voltage deviation (V_{dev}) ratio has been considered.

$$\text{Min} \quad \psi(\Upsilon_v, \Upsilon_p) = \left(k_v * \frac{max \quad (V_{sub} - V_i^{with\_DG})}{max \quad (V_{sub} - V_i^{without\_DG})} + k_p * \frac{\sum_i^{N_L} P_{loss}^{with\_DG}}{\sum_i^{N_L} P_{loss}^{without\_DG}}\right) \tag{4.3}$$

Where $$min \quad \Upsilon_v = \frac{max \quad (V_{sub} - V_i^{with\_DG})}{max \quad (V_{sub} - V_i^{without\_DG})} \tag{4.4}$$

$$\min \quad \Upsilon_p = \frac{\sum_i^{N_L} P_{loss}^{with\_DG}}{\sum_i^{N_L} P_{loss}^{without\_DG}} \tag{4.5}$$

However, the distribution planning problem has five constraints: (i) node voltage constraint, (ii) branch thermal limit constraint, (iii) DG power rating constraints (iv) Capacitor bank power rating constraints, and (v) OLTC tap ratio settings.

Networks constraints:

a) All node voltage limits

$$v^{min} \leq v_i \leq v^{max} \qquad \forall i = N_B \tag{4.6}$$

b) Thermal limits

$$I_{L\_i} \leq I_{L\_\max\_i} \qquad \forall i = N_L \tag{4.7}$$

c) DG power limits

$$P_{DG}^{min} \leq P_{DG\_i} \leq P_{DG}^{max} \qquad \forall i = N_{DG} \tag{4.8}$$

d) Capacitor bank power limits

$$Q_{CB}^{min} \leq Q_{CB\_i} \leq Q_{CB}^{max} \qquad \forall i = N_{CB} \tag{4.9}$$

e) Transformer tap setting limits

$$\alpha^{min} \leq \alpha_i \leq \alpha^{max} \qquad \forall i = N_L \tag{4.10}$$

4.4 BASIC GA OPTIMIZATION FOR DG ALLOCATION

The main objective of optimization is to identifying the sizing and location of a sets of DG to be introduced in to the distribution system. In this distribution system planning problem optimization is done by genetic algorithm to determine an economical yet reliable network with better technical features, such as lower power loss, better node voltage profile, and better branch current/thermal limit ratio while maximizing DG power (P_{DG}) in order to reduce the stress of excessive active and reactive power demand from transmission networks. Previously discussed a GA is an iterative procedure which begins with an initial population mainly which randomly generated. There are several different encoding strategy for the initial population which is depend upon the problem to be optimize. Objective function and fitness are calculated for each and every chromosome of the population. On the basis of evaluated fitness functions of the population, a set of chromosome is selected for the matting pool by the selection operators. The selection operator select the chromosome in such a way that the chromosome participate in the matting pool has better average fitness then that of initial population while maintaining the same number of population in the matting pool. The crossover and mutation operator are applied on the selected chromosome to generate new offerings. These process is repeated iteratively, as the iteration progress, in most of the cases the process find the improvement in solutions (i.e. offspring have better fitness then parents) and optimal solution is obtained. With the above description, a simple Genetic Algorithm for DG allocation problem is discussed in details as follow:

4.4.1 Coding Scheme

The success of the GA structure will lies on the coding scheme. In genetic algorithm coding can be done by two different method (i) binary coding scheme and (ii) real number coding schemes. In the study the practical coding scheme is selected for optimization process and applied in the both radial distribution networks.

In this work, both the radial distribution system have one potential nodes. And all others nodes are the load nodes. So, DG can be incorporate in any load node available in the network except potential node. Also it is applicable for capacitor bank incorporation. But in case of OLTC, it can be incorporate at any branch or in between two adjacent node of the networks.

So, in practical encoding of chromosome the location for DG and capacitor bank can be randomly selected from any node except potential node, and for OLTC can be selected randomly from any branch available in the network. The flexibility for selection of location and size/settings for DG, OLTC and capacitor bank is given for better optimization.

4.4.2 Initialization

Initialization is the generation of initial population. Here, the initial population is generated randomly which contains three optimization variables (i.e. locations and rating/settings and number of DG or OLTC or Capacitor Bank). The generated value for all decision variable is randomly generated. The DGs of different sizes (kW ratings) and CB of different sizes (kVAR ratings) to be install at the load nodes except to the substation buss. The population size, generation size, cross over probability, mutation probability effects the efficiency and performance of the algorithm. Initially in the study it considered randomly some numerical value. But for better performance of optimization later stage it is found out by multi run process with different values of optimization parameters. For easy calculation in the study minimum three and maximum decision variable is considered in one chromosome together (OLTC with DG or Capacitor Bank).

Encoding of chromosome:

In the study total three decision variable had been considered for each DG optimization, OLTC optimization, and Capacitor bank optimization as shown below.

Now in case of DG optimization:

1. Number of DG have to be consider in a string.
2. The node number of the networks where DG is to be connected/placed.
3. Corresponding DG power rating.

N_{dg}	ρ_1	ρ_2	ρ_3	ρ_4	---	ρ_n	P_1	P_2	P_2	P_3	P_4	--	P_n
Number of DG	←		DG Locations			→	←			DG Ratings			→

Now in case of Capacitor Bank optimization:

1. Number of CB have to be consider in a string.
2. The node number of the networks where CB is to be connected/placed.
3. Corresponding CB rating.

N_{CB}	ρ_1	ρ_2	ρ_3	ρ_4	---	ρ_n	Φ_1	Φ_2	Φ_2	Φ_3	Φ_4	--	Φ_n
Number of CB	←		Capacitor Bank Locations			→	←			Capacitor Bank Ratings			→

Now in case of OLTC optimization:

1. Number of OLTC had to be consider in a string.
2. Branch number of the networks where the OLTC is to be connected/placed.
3. Corresponding tap setting will be applied to the OLTC.

N_{OLTC}	ρ_1	ρ_2	ρ_3	ρ_4	---	ρ_n	α_1	α_2	α_2	α_3	α_4	--	α_n
Number of OLTC	←		OLTC Locations			→	←			OLT C Settings			→

These are the optimization variable and it is used in a single chromosome structure. Now combination of these three is shown below.

N_{dg}	ρ_1 … ρ_n	P_1 … P_n	N_{CB}	ρ_n … ρ_n	Φ_1 … Φ_n	N_{OLTC}	ρ_1 … ρ_n	α_1 … α_n
←	DG	→	←	Capacitor Bank	→	←	OLT C	→

4.4.3 Fitness Function

After generating population of required size the corresponding load flow solution with optimization variable (i.e. DG, OLTC or capacitor bank) for different cases is run to evaluate the objective function $\psi(\Upsilon_v, \Upsilon_p)$ *or* $\psi(\Upsilon_p)$ for each and every chromosome. The load flow solution, evaluation of objective function and fitness function is repeated for all the strings in the population. The procedure to determine the fitness function '$f(\psi)_i$' is very much application oriented. It is directly associated with the objective function value in the optimization problem. In the distributed generator placement problem, the objective function is the minimization of cost function. After calculating the objective function, the fitness function $f(\psi)$ is calculated using two different method as given below:

In initial stage of the project, for single-objective optimization, the fitness of the each chromosome is calculated using the method of Roulette Wheel and selection of chromosome for next generation is selected directly from it. The method is mathematically formulated as given below:

$$f(\psi)_i = \frac{\psi(\Upsilon_p)_i}{\sum \psi(\Upsilon_p)_i} \qquad i = 1,2,3 \ldots \ldots popsize \tag{4.11}$$

But later stage of project, fitness function in both single-objective as well as multi objective optimization is totally different from previous one and which gives the better performance of the optimization. Also this fitness function take a major part into the adaptive or improved genetic algorithm where the crossover and mutation probability is directly depend upon the fitness function of population.

$$f(\psi)_i = \frac{1}{1 + \psi(\Upsilon_v, \Upsilon_p)_i} \qquad i = 1,2,3 \ldots \ldots popsize \tag{4.12}$$

4.4.4 Reproduction

The first genetic algorithm operator is reproduction. This determines which chromosome of the current population will be participate in matting pool to create the next generation population. So, basically this operator is known as the selection operator for breeding. This is done by using some biased random selection approach. Hence parents are randomly selected or chosen from the current population in such a way that the 'best' strings in the population have more chance of being selected. There are so many approach is available for this selection process, such as by Boltzman selection, Roulette Wheel selection, Tournament selection, Rank selection, Truncation selection, Local selection, etc. In this work Roulette Wheel selection has been used [24]:

Reproduction operator copied an old chromosome into a mating pool. The chromosome with a higher fitness value have higher probability of being selected into mating pool and contributing one or more offspring in the next generation. One pair of matting chromosomes can generate two offspring. But in this study one offspring is considered. The following are the steps carried out for the roulette wheel selection process:

$$\lambda_i = \frac{f(\psi)_i}{\sum f(\psi)_i} \qquad i = 1,2,3 \ldots \ldots popsize \tag{4.13}$$

Step 1: Sum the fitness of all the chromosomes present in the population and named as total fitness.

Step 2: Generate a random number (k) between zero and the total fitness.

Step 3: Select a chromosome whose cumulative fitness obtained from summing its fitness to the fitness of the proceeding chromosome is greater than or equal to random number (k).

4.4.5 Crossover

The second genetic algorithm operator is crossover. Where the two selected parent chromosomes is employed in certain fashion or participate breeding process to generate single or more children who bear some of the useful genetic characteristics from both the parents. But it is expected that the offspring will bear more genetic characteristics from the best fittest parents of the matting pair. In this work single offspring is generated from one pair of parent chromosomes. The random selection technique to pick up the parents pair from the existing population is described previously in the section of reproduction. After selecting the parents, crossover can be carried out using various methods like Single Point Crossover, Multi-point Crossover or Uniform Crossover, Half-Uniform Crossover arrangements, three parents crossover.

In the present work two parents uniform crossover is used. This is illustrated in the following example. Let Parent1 and Parent2 be the two parents selected randomly for crossover. Assume the strings parent1 and parent2 as given below and, a universal crossover site is selected by generating a random number of 0 to 1 with giving same priority (0.5) for both the parents. Bothe the parents are shown in different colour for better understanding.

Parent1	N_{dg_1}	ρ_{11}	ρ_{12}	ρ_{13}	ρ_{14}	ρ_{15}	--	ρ_{1n}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	--	P_{1n}
Cross(>0.5)	Y	N	N	Y	N	Y		Y	N	N	Y	N	Y		N
Parent2	N_{dg_2}	ρ_{21}	ρ_{22}	ρ_{23}	ρ_{24}	ρ_{25}	--	ρ_{2n}	P_{21}	P_{22}	P_{23}	P_{24}	P_{25}	--	P_{2n}
	Number of DG	←			DG Locations			→	←			DG Ratings			→

For illustration the string length is taken as randomly, but in the thesis work string length depends upon the maximum number of DG, OLTC and capacitor bank to be considered into RDS.

Let the crossover site is randomly position. Then single children is generated as below.

Offspring	N_{dg_2}	ρ_{11}	ρ_{12}	ρ_{23}	ρ_{14}	ρ_{25}	--	ρ_{2n}	P_{11}	P_{12}	P_{23}	P_{14}	P_{25}	--	P_{1n}
	Number of DG	←			DG Locations			→	←			DG Ratings			→

It is seen that each crossover resulted in the children. In order to control crossover rate also there is a parameter known as "Crossover Probability(Ω_c)" which is discuss details in later stage. This probability is used as a decision variable before performing the crossover. This probability is known as the crossover rate. Crossover probability lies in the range of 0 - 1. The following steps are carried out to perform crossover.

Step 1: Form a matting pool of parent's chromosomes by randomly selection method. The size of matting pool must be same with the population size.

Step 2: Select one of the parent's pair from the matting pool and generate random number between 0 and 1.

Step 3: Set a crossover probability 'Ω_c'.

Step 4: If the randomly generated number is greater than crossover probability 'Ω_c' cross over will not occur and the offspring will contained only one parent chromosome. ***The offspring can be selected by two different method (i) best fitness parent among the parent pair and (ii) the chromosome belongs the same location or***

number of the selected parent's pair location or number in the population and matting pool respectively.

Step 5: If the randomly generated number is less than crossover probability 'Ω_c' than crossover takes place and a single offspring is generate.

4.4.6 Mutation

Selection and crossover efficiently search and recombine the surviving chromosomes. Mutation is a genetic operator which is capable of creation new genetic material in the population to maintain the population diversity. It is nothing but random alteration of chromosome variable or optimize variable (i.e. DG and capacitor bank locations, size, and OLTC locations and settings). The following example illustrates the mutation operation.

Let Mutation site is at 4th position of the string.

Crossed Offspring:

Offspring	N_{dg_2}	ρ_{11}	ρ_{12}	ρ_{23}	ρ_{14}	ρ_{25}	--	ρ_{2n}	P_{11}	P_{12}	P_{23}	P_{14}	P_{25}	--	P_{1n}
Mutate(>0.5)	N	N	N	Y	N	N		N	N	N	N	N	Y		N
	Number of DG	←		DG Locations				→	←		DG Ratings				→

Offspring after mutation

Offspring	N_{dg_2}	ρ_{11}	ρ_{12}	$\boxed{\rho_{xx}}$	ρ_{14}	ρ_{25}	--	ρ_{2n}	P_{11}	P_{12}	P_{23}	P_{14}	$\boxed{P_{xx}}$	--	P_{1n}
	Number of DG	←		DG Locations				→	←		DG Ratings				→

In the above illustration after getting the mutation site, a random value is generated from corresponding allocated value is placed at the mutation site showing (xx). Hence GA can come to better solution by using mutation. Mutation occurs during evolution according to a user-definable mutation probability. This probability should be set low. If it is set too high, the search will turn into a primitive random search. Generally the mutation probability '(Ω_m)' must be below 5%. The following steps to be carried out to perform the mutation:

Step 1: Generate random number between 0 and 1.

Step 2: Set a mutation probability '(Ω_m)'.

Step 3: If the randomly generated number is less than mutation probability ‘(Ω_m)’ than mutation is executed on the off-springs which generated after the crossover operation.

4.4.7 Elitism

When creating a new population by crossover and mutation, there are chances that the best chromosome is lost. Elitism is the name of the method that first copies the best chromosome (or few best chromosomes) to the new population. The rest of the population is constructed according to GA. Elitism can rapidly increase the performance of GA, because it prevents a loss of the best found solution.

4.4.8 Genetic Control Parameter Selection:

Genetic parameters are the entities that help to tune the performance of the genetic algorithm. The selection of values for these parameters plays an important role in obtaining an optimal solution. There are some general guidelines, which could be followed to arrive at an optimal values for these parameters. There are two basic parameters of GA - crossover probability and mutation probability. Other parameters include population size, maximum generation etc.

Population size: It is the number of chromosomes consist in population or in one generation. Genetic algorithm give very poor performance with a very small populations, because the population provides an insufficient amount of sample for gating the most optimal result and only a small search space is explored. A large population is more likely to contain representative from a large number of hyper planes. Hence GAs can perform a more informed search. As a result, a large population discourages premature convergence to suboptimal solution. On the other hand, a large population requires more evaluations per generation, possibly resulting in an unacceptably slow rate of convergence.

Crossover probability (Ω_c) : the higher the crossover rate, the more quickly new chromosome are introduced into the population. If the crossover rate is too high, high performance chromosome are discarded faster than the selection can produced improvements. If the crossover rate is low, the search may deteriorate due to the lower exploration rate.

Crossover is made in hope that new chromosomes will contain best parts of parent's chromosomes and therefore the child chromosomes will be better in the sense of fitness.

Mutation probability $(\boldsymbol{\Omega_m})$**:** If there is no mutation, offspring are generated immediately after crossover (or directly copied) without any change. Mutation generally prevents the GA from falling into local extremes. A low level of mutation serves to prevent any given bit position from getting stuck to a single value or local extremes. Also mutation should not occur very often, because then GA will in fact change to random search.

4.5 ALGORITHM FOR DG ALLOCATION

The general layout of the Loss minimization and the Genetic calculation for DGs allocation issue is discussed in the previous sections. A set of steps have been indicated beneath to tackle the DGs allocation problem:

Step 1: Read the distribution networks line data and bus data (i.e. branch impedance, real and reactive power of each load node.) and specify the DG parameters.

Step 2: Run load flow of distribution networks, and save the all node voltage and all branch current magnitudes of the networks and total power loss.

Step 3: Set GEN = 0

Step 4: Randomly generate the initial population. Where the chromosomes are representing the randomly generated values of tap number, tap positions, tap settings, DGs number, DG positions, and DG active power value, etc.

Step 5: Decode the initial population and update the load-data and bus-data (i.e. tap settings, and DG ratings.) to the networks matrixes according to their respective positions.

Step 6: Run the load flow of distribution networks with updated system data. Also calculate total power loss for each population.

Step 7: Evaluate the objective function and the fitness value for each and every chromosome.

Step 8: Perform the elitism and save the population.

Step 9: GEN = GEN + 1

Step 10: form the matting pool from initial population by using Roulette Wheel Selection procedure.

Step 11: Perform crossover on the each matting chromosome pair and generate one offspring from each parent's chromosome pair;

Step 12: Perform mutation on the offspring produced by the crossover operation.

Step 13: Decode the set of offspring and and determine the DG location and size for each chromosome.

Step 14: Run foal flow for each offspring to determine the objective function and assign fitness to each offspring.

Step 15: Perform the elitism and select the η_{pop} best chromosome from the current population and the offspring's. Replace the initial population by selected best population and use it for the next generation.

Step 16: Go to step 9, till the solution converges.

Step 17: STOP

The standard optimization procedure of DG allocation problem is shown in flowchart as shown in Figure 4.2.

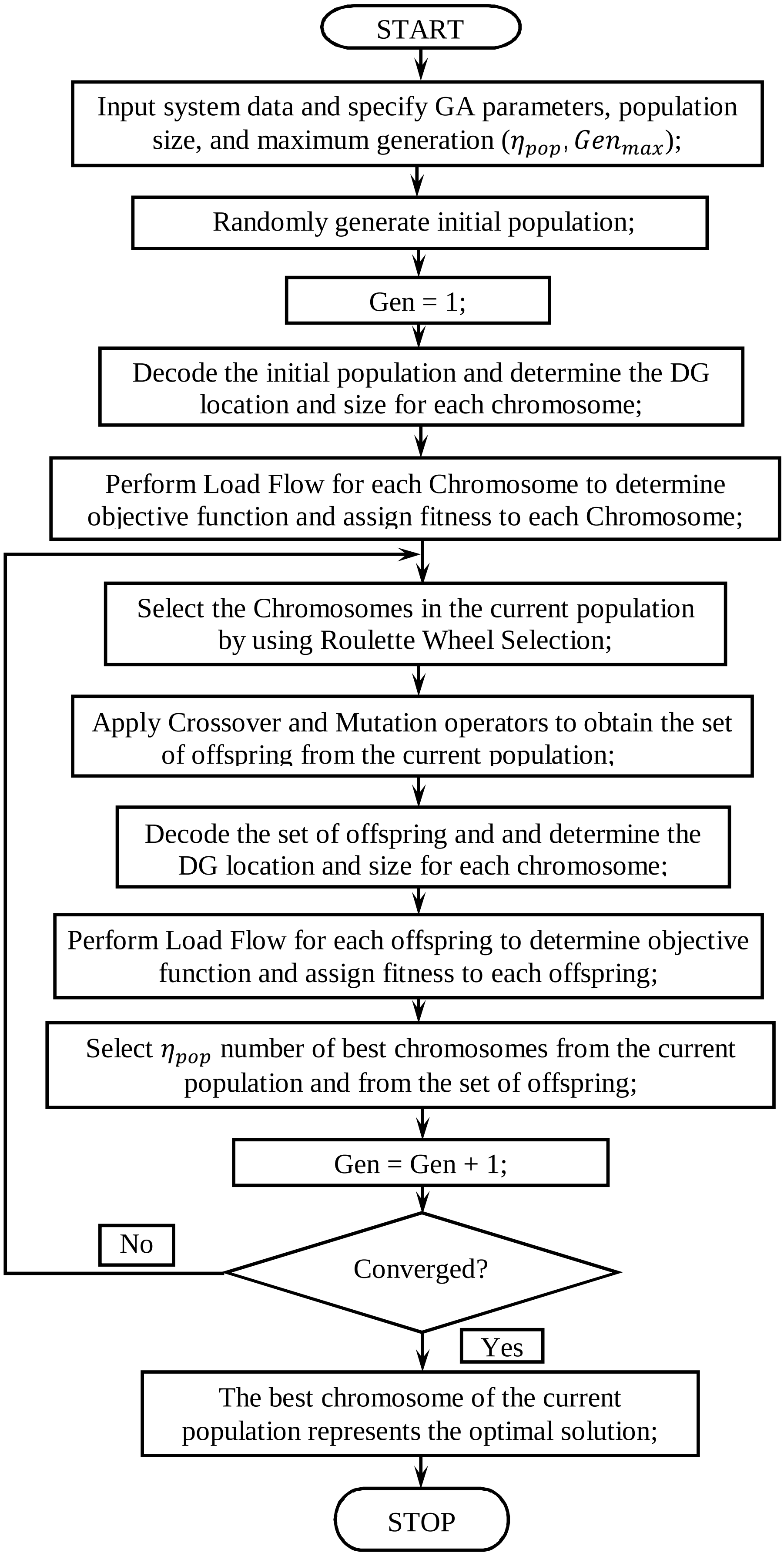


Figure 4.2. Flowchart of DG allocation with basic genetic algorithm

4.6 CASE STUDY FOR BASIC GA OPTIMIZATION

In the project work except base case total nine deferent type of case is considered while two different type of DG are considered. *Case#1(a)* distribution networks performance with only unity p.f. DGs; *Case#1(b)* distribution networks performance with only synchronous type DGs operated at 0.8 p.f; *Case#1(c)* distribution networks performance with only induction type DGs operated at 0.8 p.f; case#2 is slightly different from case#1 where OLTC is operated along with DG. *Case#2(a)* distribution networks performance with only unity p.f. DGs along OLTC; *Case#2(b)* distribution networks performance with only synchronous type DGs operated at 0.8 p.f along OLTC; *Case#2(c)* distribution networks performance with only induction type DGs operated at 0.8 p.f along OLTC; *Case#3* distribution networks performance with only capacitor banks, *Case#4* distribution networks performance with capacitor banks along OLTC; and *Case#5* Distribution networks performance with only OLTCs. So in the project three different type of DGs operating condition are considered (a) DG is operated at unity power factor, (b) DGs are operating at 0.8 power factor with giving reactive power to the distribution system (i.e. synchronous DG) and (c) DGs are operating at 0.8 power factor with consuming reactive power from the distribution system (i.e. induction type DG). All algorithm are developed in “MATLAB© 2008 coding” for this problem. First load flow is carried out for the system. All experiments are done on an Intel® Core™ i3 CPU M380 @ 2.53GHz personal computer (PC) with 6GB memory under 64bit Windows 7.

In all simulations, the following parameters have been used:

1. Minimum allowable Voltage 0.95p.u
2. Maximum allowable Voltage 1p.u
3. Maximum allowable Branch Current is 130% of its rated capacity.
4. Maximum allowable DG penetration is 50% of the total load capacity of the networks.

4.6.1 Selection of GA Parameter for DG Allocation

To know the effect of the genetic algorithm parameter on the optimization process the each and every parameter had been change for five time and the optimization process continuously run for 20 time. After completion of five cycle the data are recorded and also make a comparison. In the study four GA parameter is considered. Initially the maximum generation (Gen_{max}) parameter is varying from 50 generation to 201 generation with an increasing step of 40 generation where the other GA parameter are kept fixed, after completing the variation process 250 is selected as the optimal maximum generation for future optimization process. The next variable GA parameter is population number (η_{pop}) which is follow the previous method and after completing the variation process 170 is selected as the optimal population number for future optimization process. Similarly crossover probability (Ω_c) and mutation probability (Ω_m) are also varying with a fixed generation and population which are previously chosen by same methods. After the completing the variation process 0.9 and 0.0005 are selected as optimal crossover probability and mutation probability respectively for the future optimization process.

The four GA parameters variable value are given below and the result are shown in the Table 4.1.

1. Population size = 50 to 210 with a step of 40
2. Maximum Generation = 100 to 300 with a step of 50
3. Crossover probability 'Ω_m' = 0.9 to 0.5 with a step of 0.1
4. Mutation Probability 'Ω_m' = 0.0005 to 0.0105 with a step of 0.0025

Other parameters had been keep same for this process.

Table 4.1. GA parameter selection with system#1

Network parameter	*Tap settings limit = 0.95 to 1.05; Maximum DG power = 500kW; Minimum DG power =50 kW; DG penetration limit = 1500 kW; Maximum no. of Tap = 20; Maximum no. of DG = 10;*	*Maximum allowable line Current = 40%; Minimum Voltage Settings = 0.9 p.u.; Maximum run for GA optimization = 20; Maximum iteration for load flow = 300; Accuracy label in load flow= 10^{-9}*

Gen_{max}	η_{pop}	Ω_c	Ω_m	**Elite Power Loss (Kw)**			**Average Power Loss (Kw)**		**Minimum Fitness**	
				Minimum	**Mean Value**	**Standard Deviation**	**Mean Value**	**Standard Deviation**	**Minimum Value**	**Standard Deviation**
100	50	0.9	0.0005	37.578	67.657	13.303	105.400	15.244	0.00215	0.00121
150	50	0.9	0.0005	41.239	63.135	11.565	98.418	14.176	0.00166	0.00090
200	50	0.9	0.0005	42.772	65.236	10.937	100.310	13.830	0.00238	0.00098
250	50	0.9	0.0005	41.646	64.614	11.864	94.891	15.717	0.00288	0.00132
300	50	0.9	0.0005	43.761	63.556	10.445	93.982	14.801	0.00295	0.00093
250	*50*	0.9	0.0005	39.196	62.471	13.611	93.504	18.618	0.00245	0.00144
250	*90*	0.9	0.0005	25.791	43.281	9.639	74.661	14.123	0.00107	0.00041
250	*130*	0.9	0.0005	30.651	44.001	8.253	76.431	13.146	0.00093	0.00015
250	***170***	0.9	0.0005	25.929	37.601	7.099	67.873	11.139	0.00046	0.00018
250	*210*	0.9	0.0005	24.989	34.079	3.092	66.828	6.5806	0.00046	7.6e-005
250	170	***0.9***	0.0005	29.274	38.83	6.876	70.846	10.391	0.00057	0.00020
250	170	*0.8*	0.0005	25.182	42.943	10.020	79.116	17.193	0.00063	0.00017
250	170	*0.7*	0.0005	33.308	45.763	7.274	83.174	12.648	0.00065	0.00016
250	170	*0.6*	0.0005	30.371	49.829	10.536	87.064	16.106	0.00069	0.00013
250	170	*0.5*	0.0005	39.648	54.160	9.254	94.515	12.711	0.00072	0.00018
250	170	0.9	***0.0005***	28.943	36.208	5.065	66.532	9.7136	0.00062	0.00011
250	170	0.9	*0.0030*	23.910	35.894	8.548	65.074	14.814	0.00054	0.00015
250	170	0.9	*0.0055*	27.296	35.100	6.909	64.449	11.366	0.00058	9.6e-005
250	170	0.9	*0.0080*	22.930	35.909	7.964	64.879	11.783	0.00063	0.00011
250	170	0.9	*0.0105*	17.176	31.753	5.681	60.003	9.5657	0.00056	0.00010

4.6.2 Single-Objective Optimization with Basic GA

In this single objective optimization only power loss is consider as objective function. In this case two different objective function approach is considered. In the first approach objective is mathematically formulated as $Min\ \psi(\Upsilon_p) = \left(P_{loss}^{with\_DG}\right)$. After calculating the objective function, fitness of the population is calculated and this fitness function is directly use as selection operator. Here, minimum fitness belongs to the optimal or elite chromosome as per the fitness function. Now to minimize the losses the distributed generator is selected by genetic algorithm. The distributed generator placement results in node voltages and reduced power losses. A comparison is made between the losses of with distributed generator and without distributed generator. These objective function approach is applied on only System#1 to validate the proposed scheme with basic GA optimization.

But, in second approach objective is totally different from first one and it is mathematically formulated as $Min\ \ \psi(\Upsilon_p) = \left(\frac{\sum_i^{N_L} P_{loss}^{with\_DG}}{\sum_i^{n_L} P_{loss}^{without\_DG}}\right)$. In this approach calculation of fitness and selection of chromosomes in the matting pool is similar to the multi-objective optimization which is describe in the section (). Here, maximum fitness belongs to the optimal or elite chromosome as per the fitness function. Objective function approach is applied on both System#1 and System#2 to validate the proposed scheme with basic GA optimization.

(A) Results of First Approach

The network and GA parameter consider for this optimization is shown in Table ().

Table 4.2. Base case converged cower flow solution for system #1.

GA parameter		**Network parameter**	
Population size (η_{pop})	170	**DGs power rating range:**	50 - 500kW
Maximum Generation (Gen_{max})	250	**Tap change setting range:**	0.95 – 1.05
Crossover probability 'Ω_c'	0.9	**Maximum number of Tap:**	20
Mutation Probability 'Ω_m'	0.0005	**Maximum number of DG:**	10

Table 4.3. Comparison of various cases optimization operation.

Total no of DGs	Total DG Power (kW)	No. of Tap	Elite Power Loss (kW)	Average Power Loss (kW)	Min. Node Voltage (Volt)	Max. Node Voltage (Volt)	Elite Fitness	Max Current (Amp)	Run Time (Sec)
Base case									
0	0	0	224.45	224.45	0.9092	1	0	0.49532	0
Case#1(a)									
5	1966	0	54.685	101.08	0.96883	1	0.00113	0.33413	431.68
Case#2(a)									
6	1916	5	45.867	82.478	0.97137	1	0.00064	0.30244	441

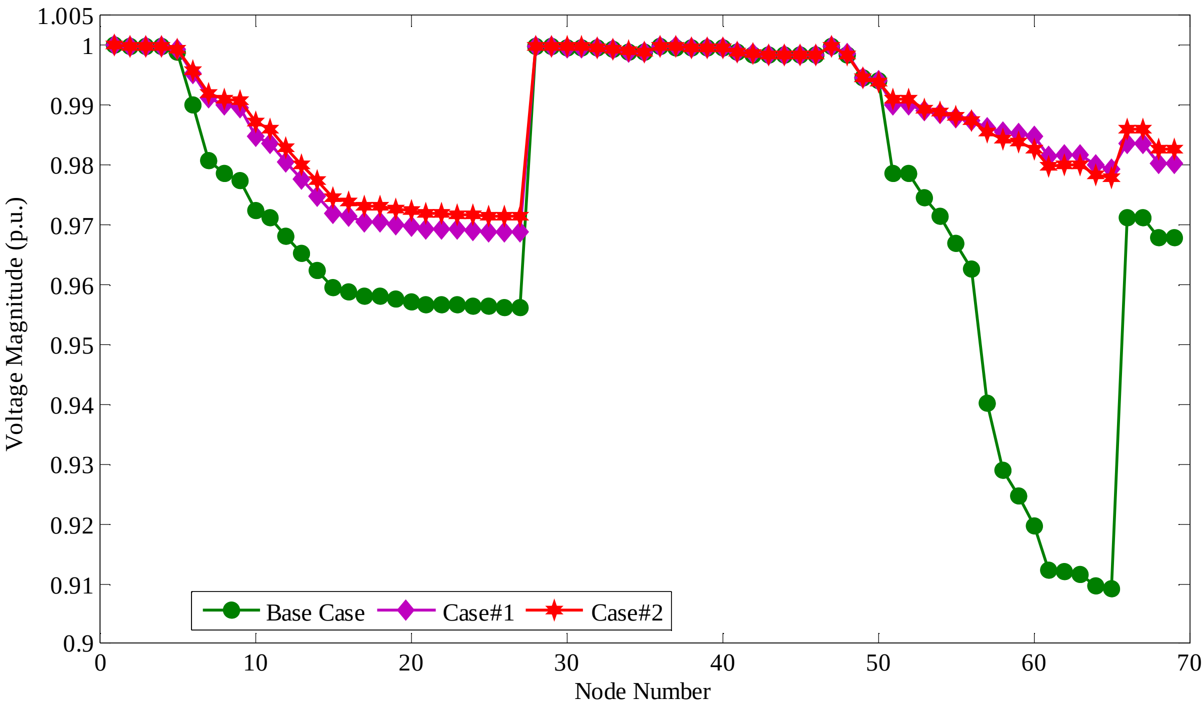


Figure 4.3. Node voltage magnitude of system#1; case#1(a), unity p.f. DG; case#2(a), unity p.f. DG and OLTC

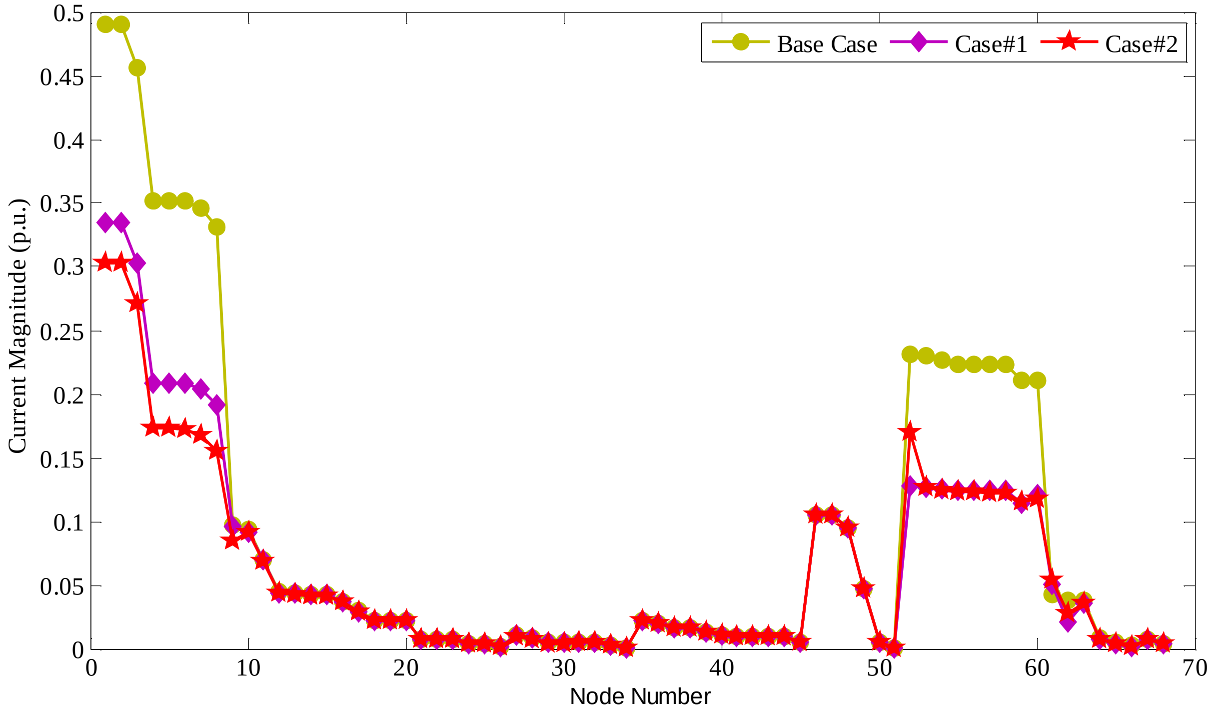


Figure 4.4. Branch current magnitude of system#1; case#1(a), unity p.f. DG; case#2(a), unity

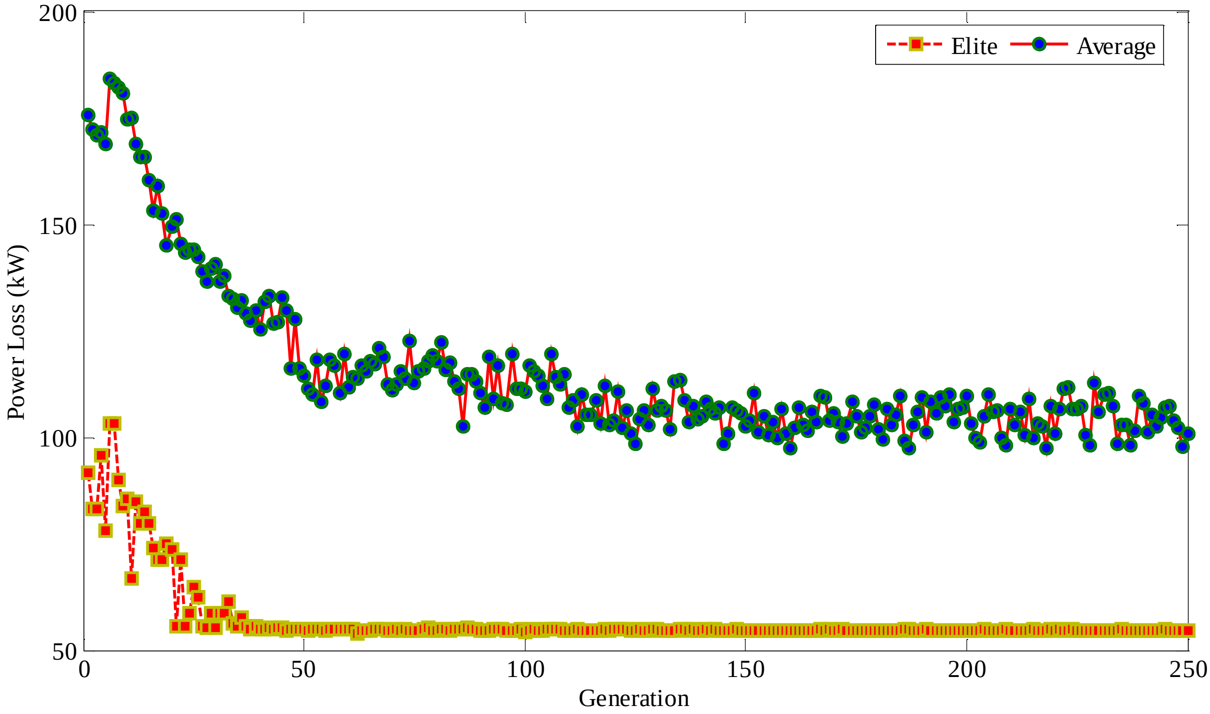


Figure 4.5. Generation wise variation of average and minimum power loss of system#1 for case#1(a) unity p.f. DG

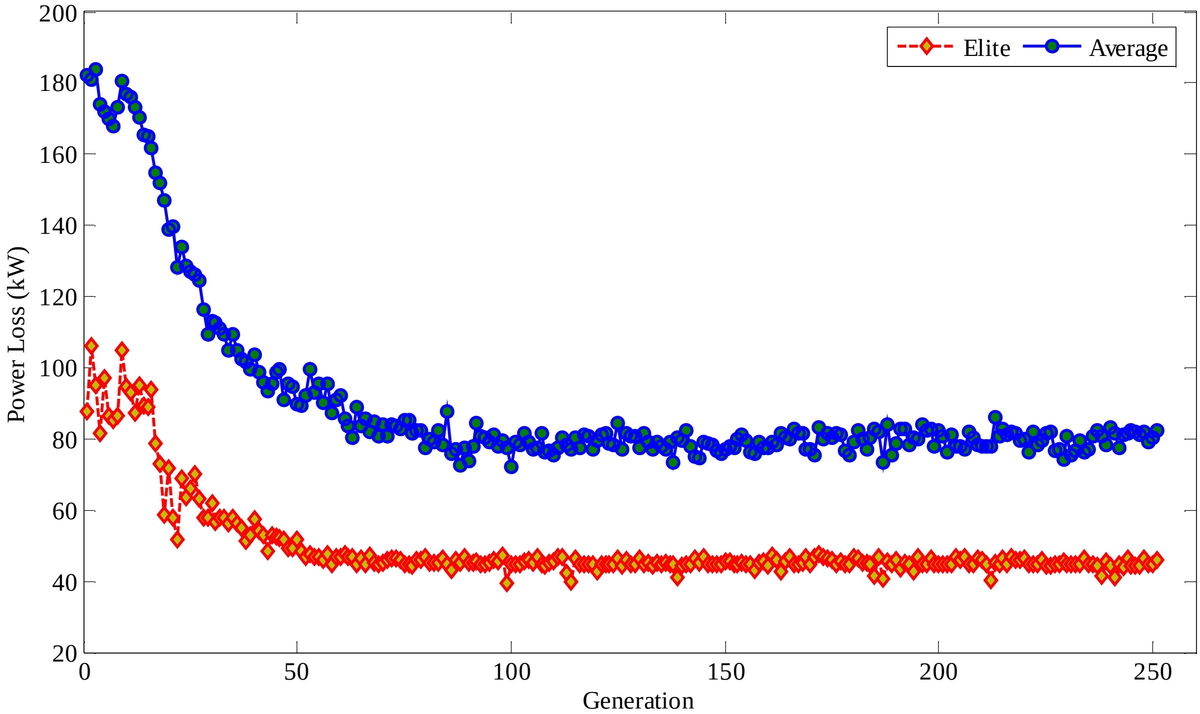


Figure 4.6. Generation wise variation of average and minimum power loss of system#1 for case#2(a) unity p.f. DG and OLTC

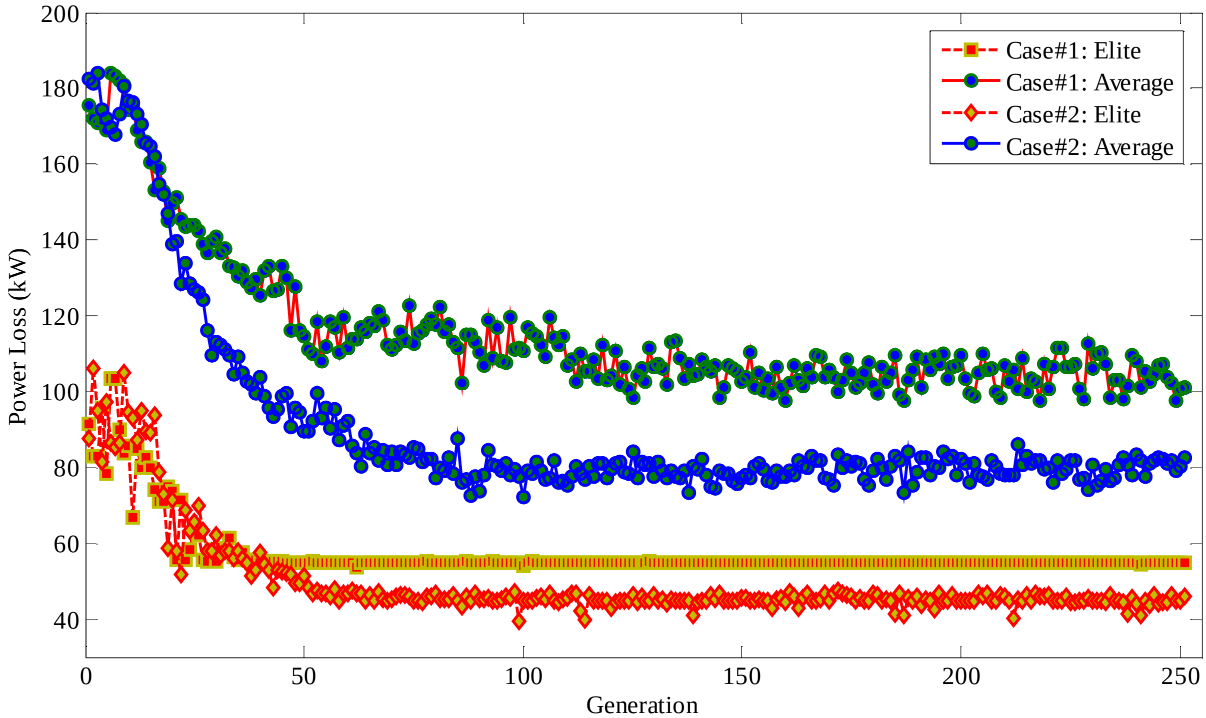


Figure 4.7. Comparison of average and minimum power loss in different cases; case#1(a), unity p.f. DG; case#2(a), unity p.f. DG and OLTC

Table 4.4. Converged Power Flow Solution of case#1(a); case#1(a), unity p.f. DG

Node/ Branch	**Voltage (p.u)**	**Angle (radian)**	**Current (p.u)**	**Node/ Branch**	**Voltage (p.u)**	**Angle (radian)**	**Current (p.u)**
1	1	0	0.33413244	36	0.999933	-2.06E-05	0.019432
2	0.9999735	-5.84E-06	0.33413244	37	0.999761	-0.00013	0.016238
3	0.9999471	-1.17E-05	0.30251104	38	0.999603	-0.00017	0.016238
4	0.9998746	-2.48E-05	0.20853272	39	0.999557	-0.00019	0.013296
5	0.9993968	0.0001323	0.20853272	40	0.999555	-0.00019	0.010354
6	0.9953527	0.0036349	0.20822975	41	0.998857	-0.00038	0.010198
7	0.9911637	0.0073101	0.20392146	42	0.998565	-0.00046	0.010198
8	0.990184	0.0081982	0.19176452	43	0.998526	-0.00047	0.009459
9	0.9897113	0.0086662	0.09547209	44	0.998518	-0.00047	0.009459
10	0.9847748	0.0101099	0.09203603	45	0.998419	-0.00051	0.00473
11	0.9836639	0.0103954	0.0693878	46	0.998419	-0.00051	0.104766
12	0.9805428	0.0112947	0.04418254	47	0.999825	-5.64E-05	0.104766
13	0.9776548	0.0120857	0.04318975	48	0.998579	-0.00084	0.095045
14	0.974793	0.0128718	0.04219404	49	0.994734	-0.00327	0.047536
15	0.9719599	0.0136532	0.04219404	50	0.994189	-0.00361	0.005444
16	0.9714335	0.0137988	0.03658378	51	0.990149	0.008203	0.000454
17	0.9705642	0.0140395	0.02943985	52	0.99014	0.008206	0.12738
18	0.9705555	0.014042	0.02230417	53	0.989243	0.010161	0.127105
19	0.9700964	0.014187	0.02230417	54	0.988707	0.011906	0.1257
20	0.9698013	0.0142804	0.02218428	55	0.988027	0.014341	0.124497
21	0.9693253	0.0144313	0.00775709	56	0.987417	0.016746	0.124497
22	0.9693185	0.0144334	0.00710225	57	0.986166	0.029887	0.124497
23	0.9692476	0.0144561	0.00710225	58	0.985613	0.036376	0.124497
24	0.9690932	0.0145056	0.00355158	59	0.98542	0.038894	0.113671
25	0.9689228	0.014554	0.00355158	60	0.984732	0.041714	0.120885
26	0.968854	0.0145761	0.00177581	61	0.981589	0.044692	0.050929
27	0.9688347	0.0145823	0.01124013	62	0.981793	0.044979	0.020997
28	0.9999402	-1.61E-05	0.00804314	63	0.981722	0.045183	0.035853
29	0.9998685	-6.14E-05	0.00484593	64	0.979958	0.045452	0.007394
30	0.9997473	-2.43E-05	0.00484593	65	0.979425	0.045533	0.004515
31	0.999726	-1.78E-05	0.00484593	66	0.983608	0.010415	0.002257
32	0.9996191	1.50E-05	0.00484593	67	0.983607	0.010415	0.007021
33	0.9993629	9.22E-05	0.00312438	68	0.980217	0.011398	0.00351
34	0.9990274	0.0001944	0.00072186	69	0.980216	0.011398	
35	0.99896	0.0002129	0.02262588				

Table 4.5. Converged Power Flow Solution of case#2(a); case#2(a), unity p.f. DG and OLTC

Node/ Branch	Voltage (p.u)	Angle (radian)	Current (p.u)	Node/ Branch	Voltage (p.u)	Angle (radian)	Current (p.u)
1	1	0	0.30243529	36	0.999939	-2.40E-05	0.019432
2	0.9999766	-7.50E-06	0.30243529	37	0.999768	-0.00014	0.016238
3	0.9999533	-1.50E-05	0.27137821	38	0.999609	-0.00018	0.016238
4	0.9998897	-3.29E-05	0.17303922	39	0.999563	-0.00019	0.013296
5	0.9994811	5.19E-05	0.17303922	40	0.999561	-0.00019	0.010354
6	0.9958186	0.0025579	0.17272026	41	0.998864	-0.00038	0.010198
7	0.9920205	0.0051847	0.16813566	42	0.998571	-0.00046	0.010198
8	0.9911346	0.0058175	0.15510393	43	0.998532	-0.00047	0.009459
9	0.9907117	0.0061488	0.08447434	44	0.998524	-0.00048	0.009459
10	0.9872132	0.002859	0.09110796	45	0.998426	-0.00051	0.00473
11	0.9861106	0.0031288	0.0685247	46	0.998425	-0.00051	0.104783
12	0.9830159	0.003969	0.04340238	47	0.99984	-6.45E-05	0.104783
13	0.9801619	0.0046764	0.04241291	48	0.998401	-0.00111	0.095062
14	0.9773343	0.0053773	0.04142059	49	0.994555	-0.00354	0.047544
15	0.9745356	0.006072	0.04142059	50	0.99401	-0.00389	0.005439
16	0.973966	0.0060883	0.03648832	51	0.9911	0.005823	0.000454
17	0.973099	0.0063277	0.029363	52	0.99109	0.005826	0.169748
18	0.9730902	0.0063301	0.02224591	53	0.989469	0.008067	0.1263
19	0.9726323	0.0064744	0.02224591	54	0.988871	0.009779	0.124781
20	0.972338	0.0065673	0.02212633	55	0.988103	0.012167	0.123472
21	0.9718633	0.0067174	0.00773682	56	0.987406	0.014526	0.123472
22	0.9718565	0.0067196	0.00708369	57	0.985659	0.027503	0.121986
23	0.9717858	0.0067422	0.00708369	58	0.984392	0.033759	0.121986
24	0.9716318	0.0067913	0.0035423	59	0.983922	0.036191	0.115129
25	0.9714619	0.0068395	0.0035423	60	0.982657	0.038843	0.117693
26	0.9713932	0.0068615	0.00177117	61	0.97987	0.042021	0.05422
27	0.9713739	0.0068676	0.01019768	62	0.980096	0.042319	0.028284
28	0.9999477	-1.99E-05	0.00706337	63	0.980173	0.042601	0.035909
29	0.9998959	-7.34E-05	0.00402867	64	0.978406	0.042871	0.007406
30	0.9997914	-8.67E-05	0.00402867	65	0.977872	0.042952	0.004504
31	0.9997714	-1.01E-04	0.00484571	66	0.986055	0.003148	0.002252
32	0.9996645	-6.80E-05	0.00484571	67	0.986054	0.003148	0.007003
33	0.9994083	9.25E-06	0.00312424	68	0.982691	0.004072	0.003502
34	0.9990728	0.0001114	0.00072183	69	0.98269	0.004072	
35	0.9990054	0.00013	0.02262574				

Multiple Run Optimal Solution for first approach:

Optimization result for 10 run:

Table 4.6. Optimal Power Flow Solutions for 10 run.

Total no of DGs	**Total DG Power (kW)**	**No. of Tap**	**Elite Power Loss (kW)**	**Average Power Loss (kW)**	**Min. Node Voltage (Volt)**	**Max. Node Voltage (Volt)**	**Elite Fitness**	**Max Current (Amp)**
Case#2(a), impact of unity p.f. DG and OLTC into the system								
5	2098	19	26.401	48.900	0.97368	1	0.00060	0.25723
4	2188	18	20.598	44.606	0.97412	1	0.00064	0.21012
4	2125	14	31.470	62.851	0.9117	1	0.00057	0.26984
4	2156	13	30.714	67.830	0.9182	1	0.00050	0.26116
4	2177	19	18.748	53.117	0.97327	1	0.00061	0.24902
4	2184	19	23.821	51.535	0.97315	1	0.00066	0.25722
3	2027	16	26.650	56.750	0.97354	1	0.00049	0.26048
3	2047	17	43.911	67.370	0.96820	1	0.00092	0.31372
4	2091	17	19.364	51.390	0.97436	1	0.00052	0.23411
3	1962	18	29.133	60.029	0.97104	1	0.00071	0.22457
Base case								
0	0	0	224.45	224.45	0.9092	1	0	0.49532

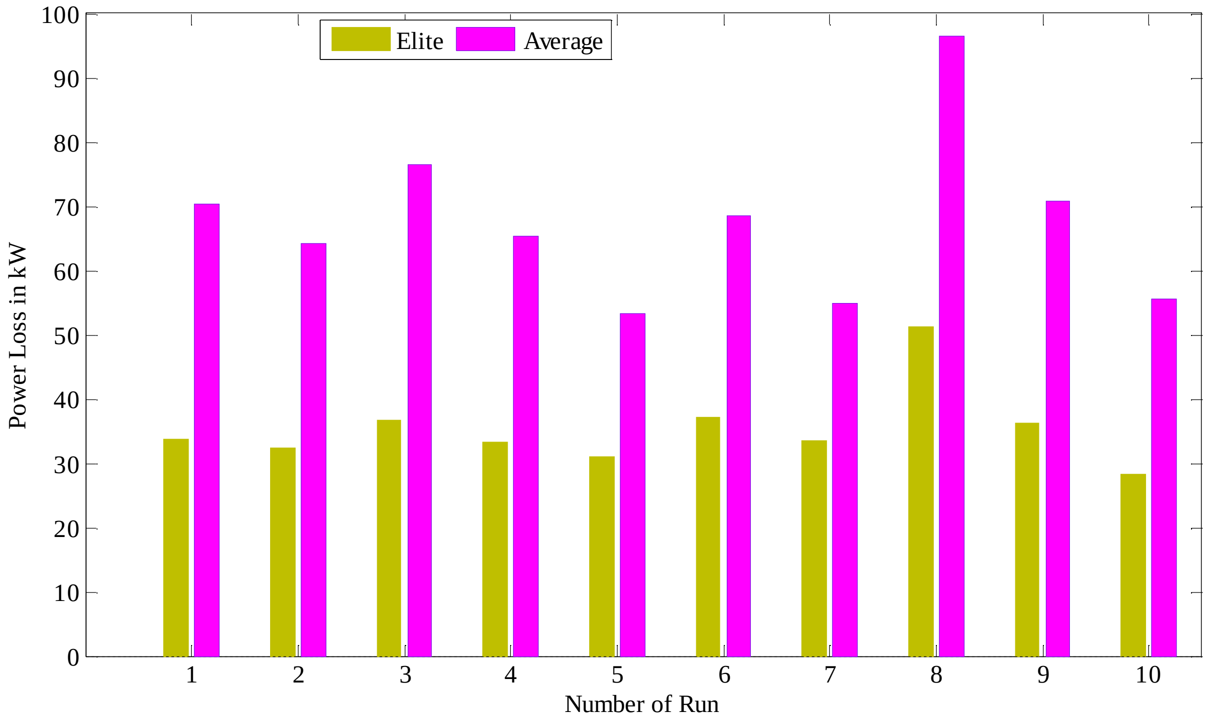


Figure 4.8. Run wise variation of minimum and average power losses

(B) Results of Second Approach

Table 4.7. Comparison of various cases optimization operation.

System	Total no of DGs	Total DG Power (kW)	No. of Tap	Elite Power Loss (kW)	Average Power Loss (kW)	Min. Node Voltage (Volt)	Max. Node Voltage (Volt)	Elite Fitness	Max Current (Amp)
System#1	*Base case*								
	0	0	0	224.45	224.45	0.90920	1	0	0.49532
	Case#1(a), impact of unity p.f. DG into the system								
	5	1957	0	55.895	56.024	0.96877	1	0.80101	0.33487
	Case#2(a), impact of unity p.f. DG and OLTC into the system								
	5	1957	13	21.698	22.051	0.97401	1	0.91204	0.26307
System#2	*Base case*								
	0	0	0	887.057	887.057	0.68445	1	0	2.4380
	Case#1(a), impact of unity p.f. DG into the system								
	6	1951	0	118.63	119.05	0.90012	1	0.88204	1.3091
	Case#2(a), impact of unity p.f. DG and OLTC into the system								
	6	1950	15	110.01	110.57	0.88322	1	0.88966	1.3036

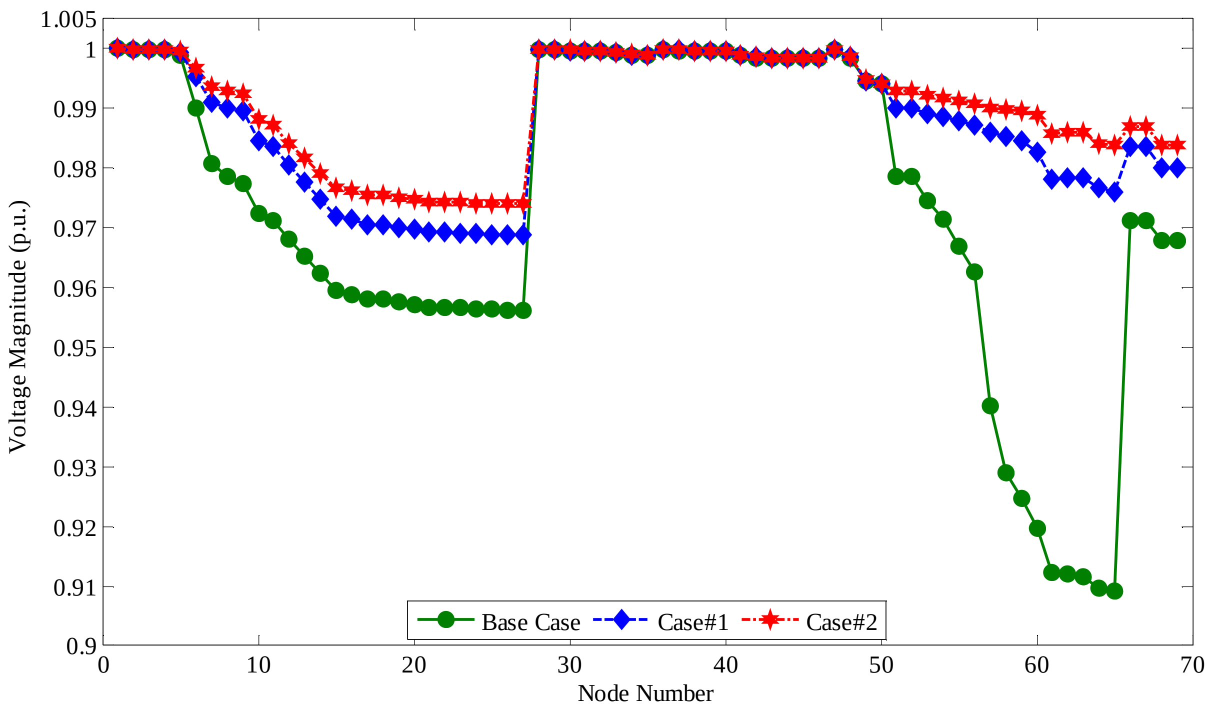


Figure 4.9. Node voltage magnitude of system#1; case#1(a), unity p.f. DG; case#2(a), unity p.f. DG and OLTC

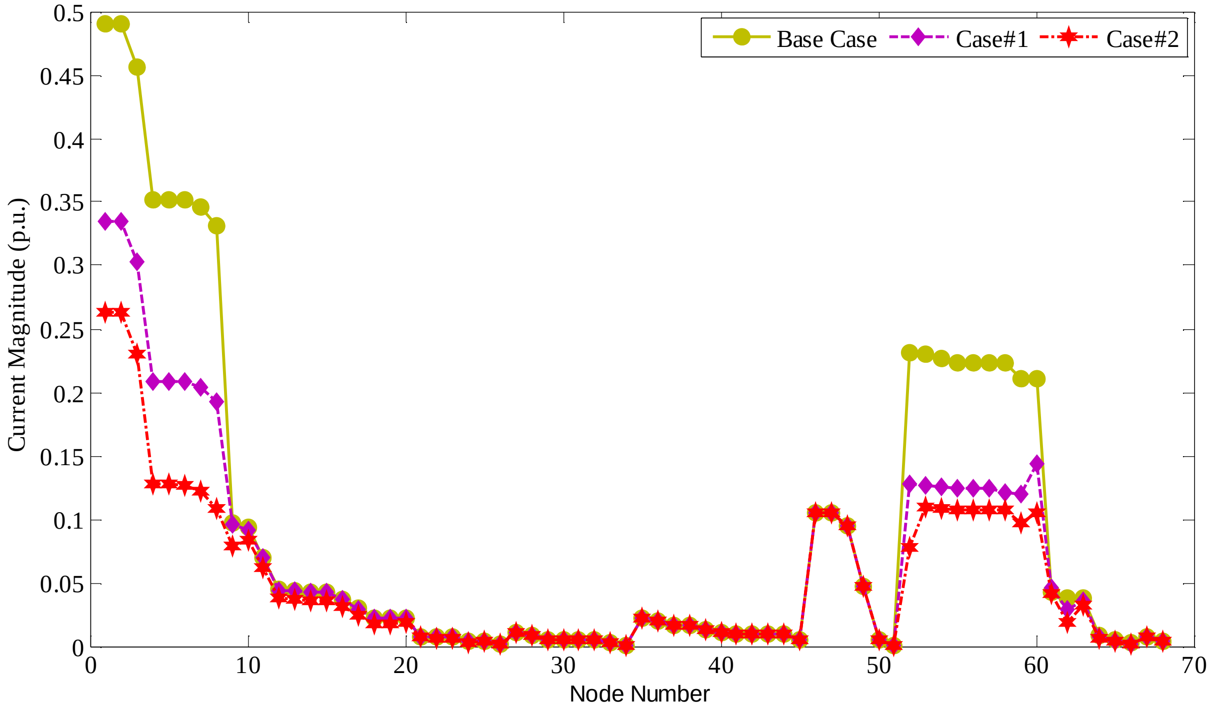


Figure 4.10. Branch current magnitude of system#1; case#1(a), unity p.f. DG; case#2(a),

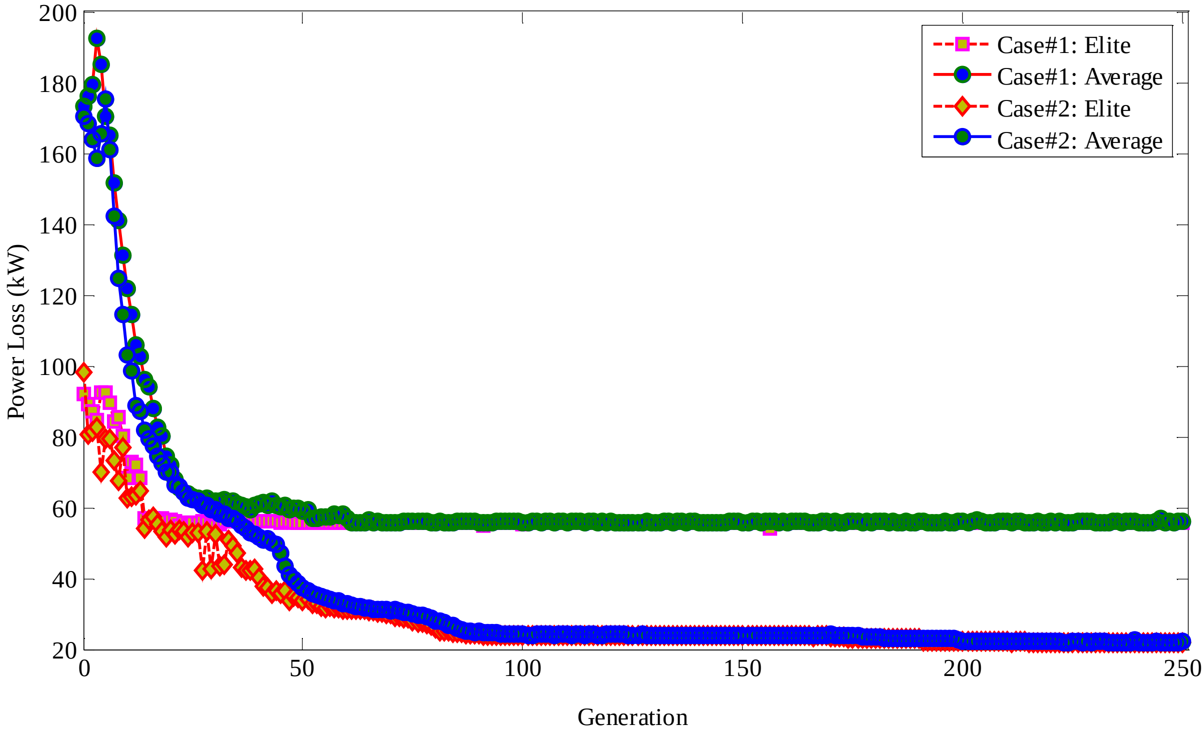


Figure 4.11. Comparison of average and minimum power loss in different cases; case#1(a), unity p.f. DG; case#2(a), unity p.f. DG and OLTC

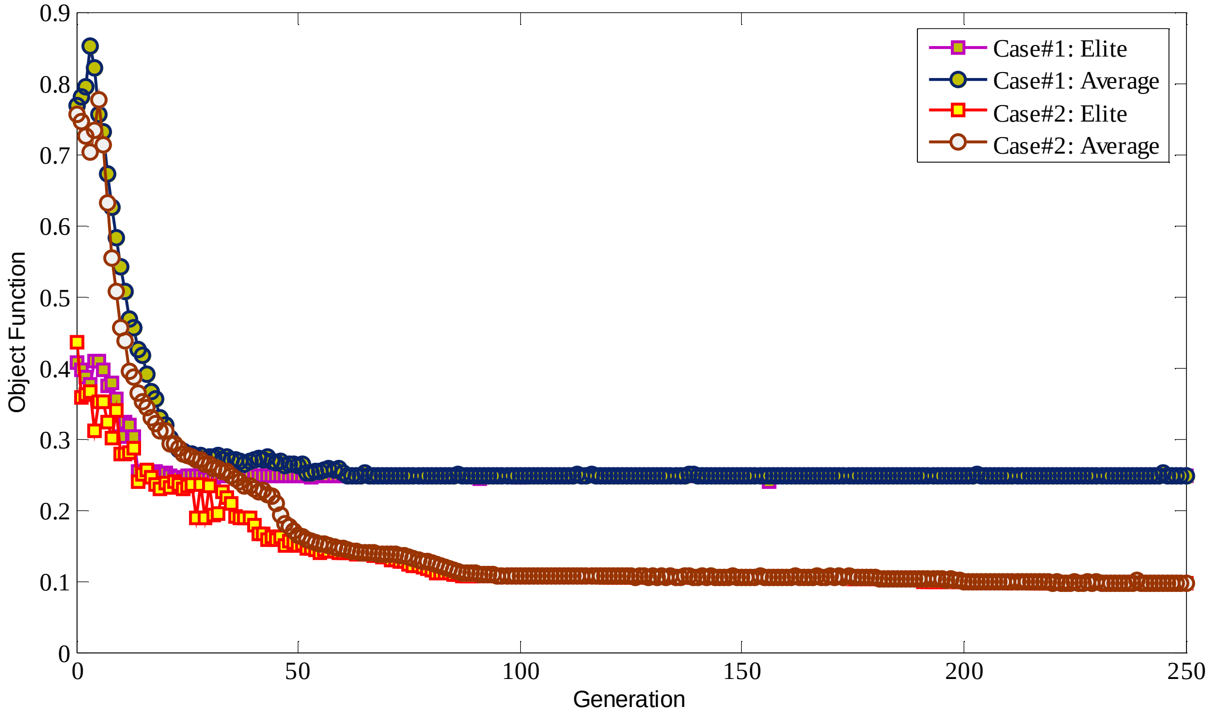


Figure 4.12. Comparison of average and minimum objective function in different cases; case#1(a), unity p.f. DG; case#2(a), unity p.f. DG and OLTC

Multiple Run Optimal Solution of Second Approach:

Optimization result for 10 run:

Table 4.8. Converged Power Flow Solution for 10 run.

Total no of DGs	Total DG Power (kW)	No. of Tap	Elite Power Loss (kW)	Average Power Loss (kW)	Min. Node Voltage (Volt)	Max. Node Voltage (Volt)	Elite Fitness	Max Current (Amp)
Case#2(a), impact of unity p.f. DG and OLTC into the system								
5	2328	10	21.616	30.115	0.98810	1	0.88288	0.23486
5	2330	10	28.663	28.937	0.98182	1	0.85925	0.27798
5	2318	8	23.824	23.831	0.97705	1	0.84798	0.28470
5	2317	10	21.582	25.638	0.98137	1	0.6331	0.27641
6	2330	10	33.842	33.936	0.98741	1	0.87373	0.27789
5	2329	7	28.126	32.139	0.98053	1	0.84841	0.28801
5	2330	9	31.495	34.354	0.98644	1	0.87361	0.22488
5	2328	10	31.254	31.687	0.98503	1	0.86817	0.27552
6	2330	10	33.399	33.553	0.98654	1	0.87084	0.27644
6	2321	9	26.028	26.062	0.98875	1	0.89304	0.21810
Base case								
0	0	0	224.45	224.45	0.9092	1	0	0.49532

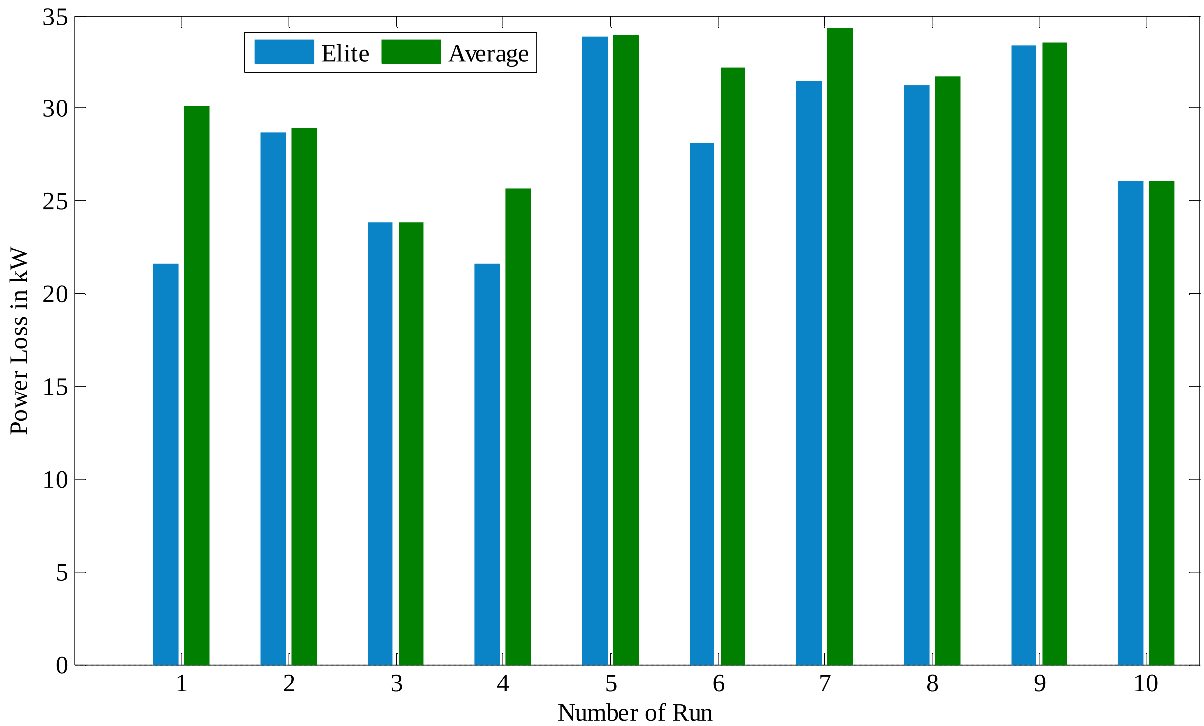


Figure 4.13. Run wise variation of minimum and average power losses

4.6.3 Multi-Objective Optimization with Basic GA

The main objective of this multi-objective optimization is to determine an economical and reliable network with better technical features, such as lower power loss, better node voltage profile, and better branch current/thermal limit ratio. Thus, two objective function are formulated as (i) the total power loss (P_{loss}) of the distribution network and (ii) maximum node voltage deviation (V_{dev}) ratio. These multi-objective function approach is applied on both System#1 and System#2 to validate the proposed scheme with basic GA optimization. The GA parameter and network constraints consider for this optimization is shown in Table (4.9).

Table 4.9. GA and network parameters considered for the optimization process

GA parameter		Network parameter	
Population size (η_{pop})	100	DGs power rating range (P_{DG}):	50 - 600kW
Maximum Generation (Gen_{max})	300	Tap change setting range(α):	System#1 = 0.94 – 1.06 System#2 = 0.90 – 1.10
Crossover probability 'Ω_c'	0.9	Maximum number of Tap:	System#1 = 10 System#2 = 20
Mutation Probability 'Ω_m'	0.0005	Maximum number of DG/Capacitor bank:	10

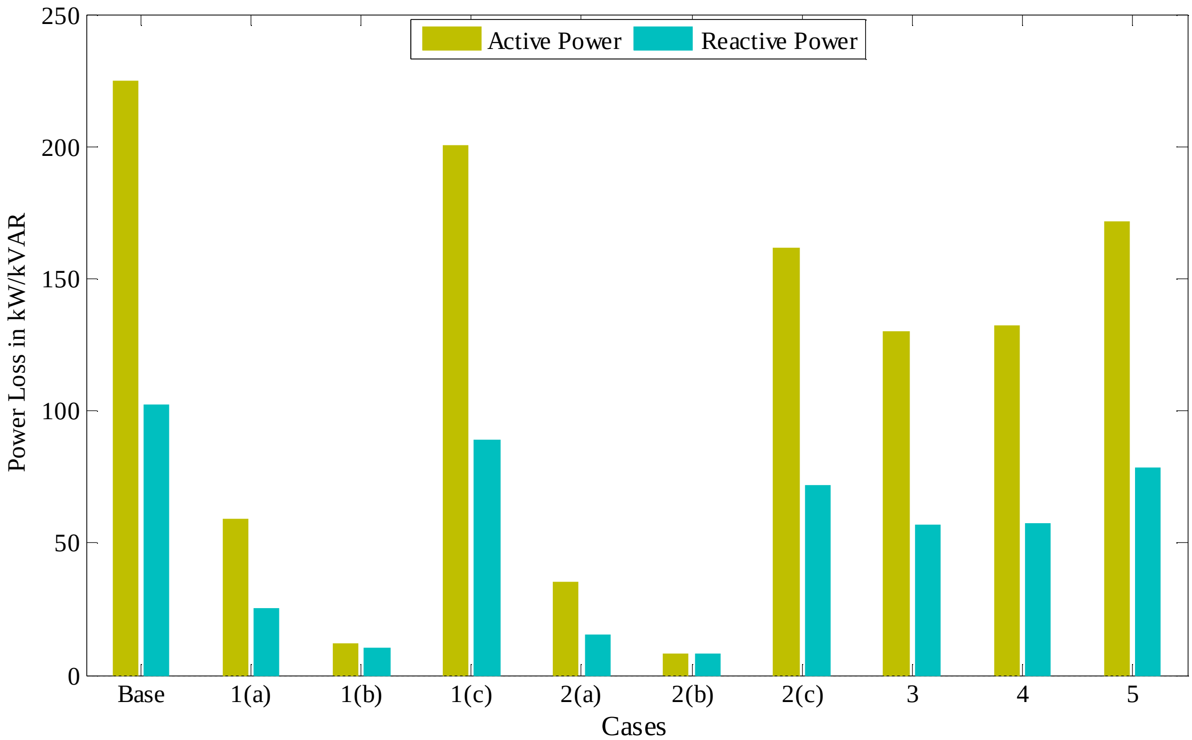


Figure 4.14. Variation of optimal active and reactive power loss of system#1

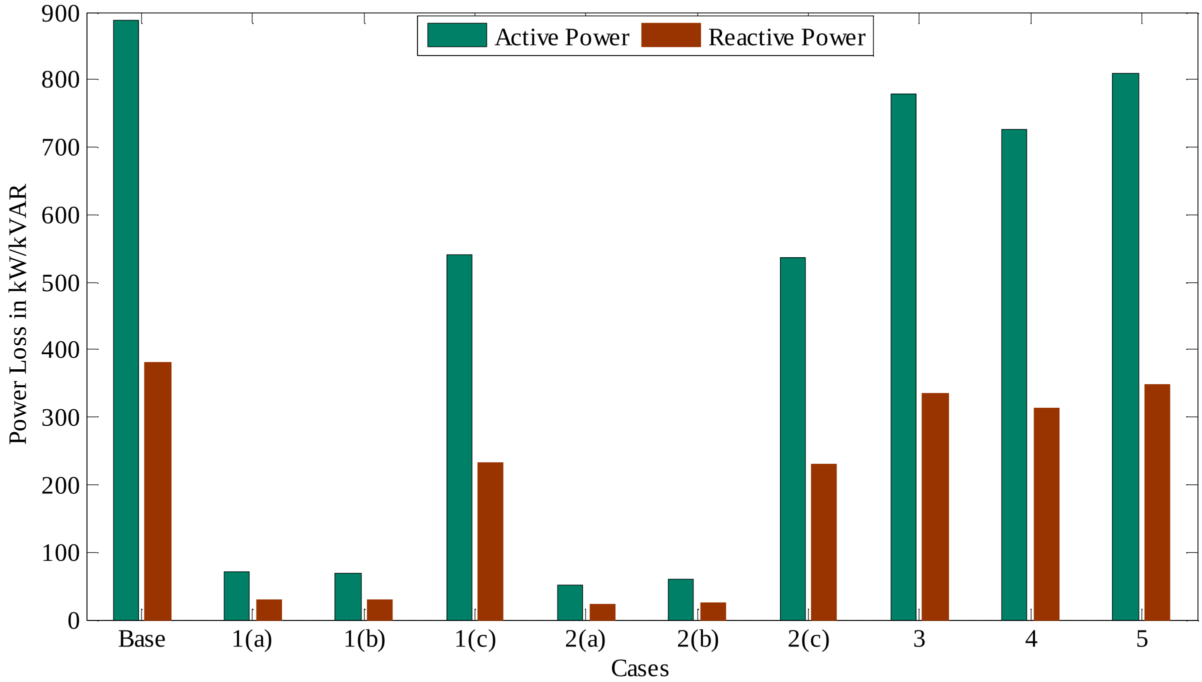


Figure 4.15. Variation of optimal active and reactive power loss of system#2

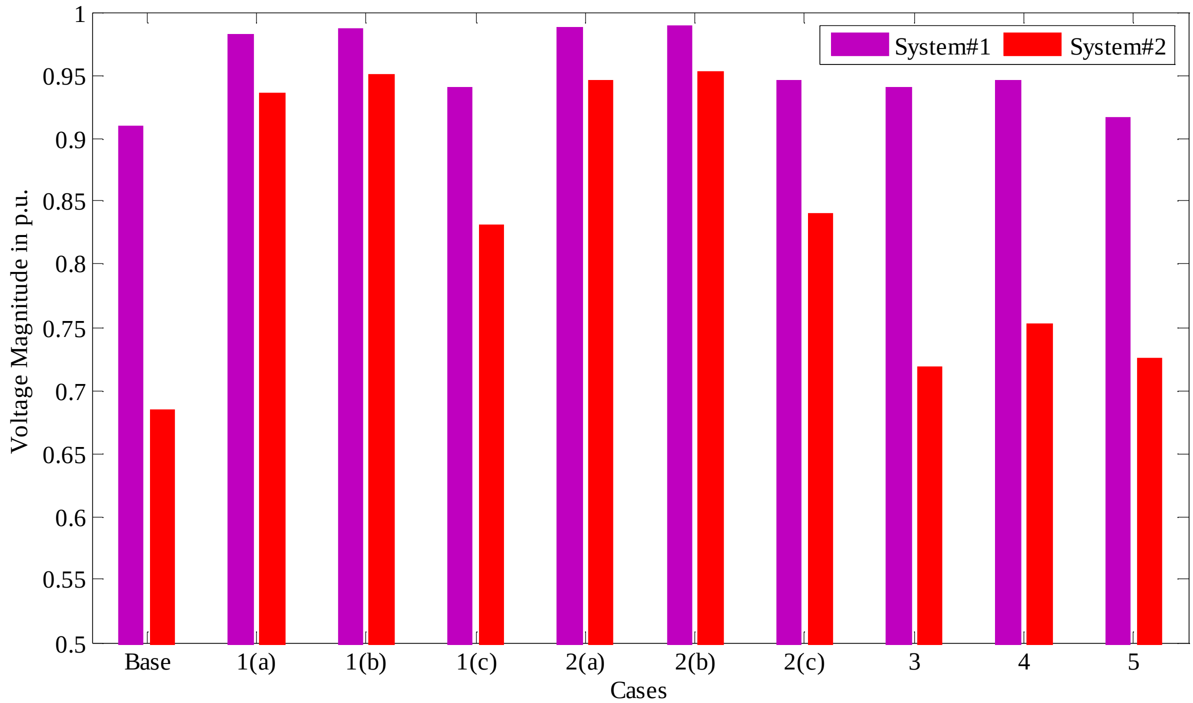


Figure 4.16. Variation of minimum node voltage of system#1 and system#2

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

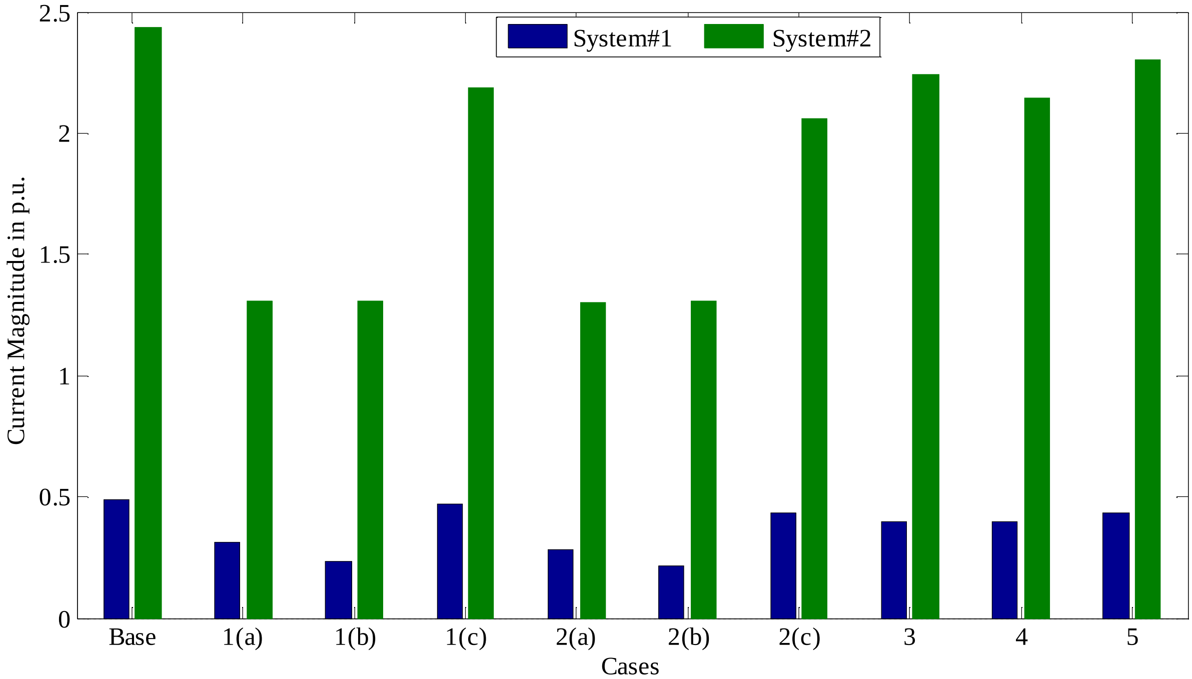


Figure 4.17. Variation of maximum branch current of system#1 and system#2

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

Multiple Run Optimized Load Flow Solution

Table 4.10. Multiple run solution for different case with system#2

Case	Minimum Active Power Loss (kW)			Average Active Power Loss (kW)		Minimum Voltage			Average Objective Function	
	Elite	Mean Value	Standard Deviation	Mean Value	Standard Deviation	Minimum Value	Mean Value	Standard Deviation	Mean Value	Standard Deviation
1(a)	57.263	72.875	9.117	73.33	9.305	0.93084	0.94027	0.004699	0.13639	0.005399
1(b)	65.103	69.613	2.589	69.71	2.544	0.94078	0.94993	0.002367	0.11877	0.004685
1(c)	507.9	556.56	21.330	562.73	18.613	0.81280	0.83233	0.006841	0.58308	0.006356
2(a)	42.994	58.747	10.267	59.195	10.329	0.92600	0.94250	0.004800	0.12490	0.006800
2(b)	57.371	62.750	3.362	63.085	3.281	0.94750	0.95270	0.001800	0.11090	0.004100
2(c)	469.96	510.137	20.057	515.82	17.268	0.80040	0.84240	0.010700	0.54080	0.012500
3	778.38	778.66	0.1555	778.69	0.1505	0.71868	0.71887	0.000117	0.88440	0.000254
4	716.52	722.59	3.329	722.88	3.647	0.78700	0.79550	0.001600	0.79590	0.004300
5	799.21	807.65	4.518	807.83	4.452	0.72531	0.72784	0.001419	0.88668	0.004574

Table 4.11. Multi-objective optimization for different system with basic GA optimization

Different Cases	Different systems	No. of DG	Total DG Power		No. of Tap	No. of CB	Total CB Reactive Power (kW)	Optimal Active Power Loss (kW)	Optimal Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
			Active Power (kW)	Reactive Power (kVAR)							
Base	System # 1	-	-	-	-	-	-	224.995	102.198	0.90919	0.49031
	System # 2	-	-	-	-	-	-	887.181	381.694	0.68442	2.43820
Case # 1 (a)	System # 1	6	2328.0	-	-	-	-	58.796	25.465	0.98262	0.31404
	System # 2	6	2323.0	-	-	-	-	70.072	30.147	0.93635	1.30910
Case # 1 (b)	System # 1	6	1864.0	1398.0	-	-	-	12.18	10.486	0.98747	0.23480
	System # 2	6	1858.4	1393.8	-	-	-	68.732	29.571	0.95001	1.30910
Case # 1 (c)	System # 1	4	1639.2	-1229.4	-	-	-	200.212	88.861	0.94072	0.46945
	System # 2	7	1836.8	-1377.6	-	-	-	540.792	232.666	0.83178	2.18770
Case # 2 (a)	System # 1	5	2325.0	-	10	-	-	35.003	15.000	0.98751	0.28087
	System # 2	7	2322.0	-	19	-	-	51.265	22.056	0.94570	1.30270
Case # 2 (b)	System # 1	6	1863.2	1397.4	9	-	-	8.052	8.303	0.98946	0.21720
	System # 2	6	1858.4	1393.8	19	-	-	59.235	25.485	0.95292	1.30520
Case # 2 (c)	System # 1	3	1433.6	-1075.2	10	-	-	161.553	71.863	0.94630	0.43166
	System # 2	6	1854.4	-1390.8	15	-	-	535.240	230.278	0.84044	2.05950
Case # 3	System # 1	-	-	-	-	4	2329.0	130.231	56.850	0.94073	0.40015
	System # 2	-	-	-	-	5	2324.0	778.845	335.085	0.71878	2.24170
Case # 4	System # 1	-	-	-	8	4	2320.0	132.456	57.386	0.94586	0.39830
	System # 2	-	-	-	19	5	2324.0	726.877	312.726	0.75302	2.14780
Case # 5	System # 1	-	-	-	10	-	-	171.446	78.606	0.91679	0.43205
	System # 2	-	-	-	20	-	-	809.771	348.390	0.72612	2.30250

From the Figure 4.14 and Figure 4.15 shows that DG placement in the distribution system is profitable. From the above result it can be concluded that the multi-objective optimization give the better optimal result then the single-objective optimization. In this multi-objective optimization, priority of each objective function can defined separately. In the case study the priority for each objective function is same.

4.7 IMPROVED GENETIC ALGORITHM (IGA) OPTIMIZATION

The traditional crossover like partly matched crossover, order crossover and cycle crossover, etc. and mutation would make some unfeasible solution to be created. In the traditional crossover and mutation, crossover probability and mutation probability are not adaptive in nature and which have no flexibility. For this reason when a basic GA optimization process trapped in a local minima these crossover and mutation probability cannot emerge from the local minima and GA optimization give a premature result. In the project study some different type of crossover and mutation method is considered to resolve all this problem. Also an adaptive crossover probability is proposed.

GA#1: In [76], based on the mechanism of biological DNA genetic information and evolution, a modified genetic algorithm (MDNA-GA) is proposed. They proposed a new mutation named adaptive mutation probability which is dynamically adjusted by considering a measure called Diversity Index (DI). It is defined to indicate the premature convergence degree of the population.

$$f_{avg} = \frac{1}{popsize} \sum_{i=1}^{popsize} f_i \tag{4.14}$$

Accordingly [22], the mutation probability is changed according to the following equation:

$$\Omega_m = 0.5 * (1 - \frac{Gen}{MaxGen})^2 * DI \tag{4.15}$$

GA#2: In [77], an Improved Genetic Algorithm (IGA) is proposed. The self-adaptive process have been employed for crossover and mutation probability in order to improve crossover and mutation quality. The crossover probability and mutation probability is controlled by evolutionary degree and is defined by Eq. (4.16) and (4.17).

$$\Omega_c = 0.9 - 0.3 * \frac{(f_c - f_{avg})}{(f_{max} - f_{avg})}, \qquad f_c \geq f_{avg} \tag{4.16a}$$

$$\Omega_c = 0.9, \qquad f_c < f_{avg} \tag{4.16b}$$

$$\Omega_m = 0.1 - 0.099 * \frac{(f_{max} - f_m)}{(f_{max} - f_{avg})}, \qquad f_m \geq f_{avg} \tag{4.17a}$$

$$\Omega_m = 0.1, \qquad f_m < f_{avg} \tag{4.17b}$$

Where, f_{max} is the optimum adaptation degree of the father population, f_{avg} is the average adaptation degree of the whole population, f_c is the better of the adaptation degree between two individuals, and f_m is the fitness degree of the mutating individuals.

GA#3: In [78], an Improved Genetic Algorithm (IGA) based on hormone modulation mechanism is proposed. In order to accelerate evolutional speed and enlarge searching scope an adaptive crossover and mutation probability employed and referring to Eq. (4.18) and (4.19).

$$\Omega_c = \Omega_0 * (1 + \alpha * \frac{(f_{avg})^{n_c}}{(f_{max}-f_{min})^{n_c} + (f_{avg})^{n_c}}) \tag{4.18}$$

$$\Omega_m = \Omega_0 * (1 + \beta * \frac{(f_{avg})^{n_m}}{(f_{max}-f_{min})^{n_m} + (f_{avg})^{n_m}}) \tag{4.19}$$

Where, pC_0 *and* pM_0 represent initial crossover probability and mutation probability respectively, f_{max}, f_{avg} *and* f_{min} represent the maximal fitness, average fitness and minimal fitness of the individual of each generation respectively. α, β, n_c *and* n_m are coefficient factors.

GA#4: The adaptive approaches proposed by Vedat Toğan and Ayşe T. Daloğlu [79] for crossover and mutation operator of the GA are as follows:

$$\Omega_c = \frac{(f_{max}-f_c)}{(f_{max}-f_{avg})}, \qquad f_c \geq f_{avg} \tag{4.20a}$$

$$\Omega_c = 0.1 * f_c, \qquad f_c < f_{avg} \tag{4.20b}$$

$$\Omega_m = 0.5 * \frac{(f_{max}-f_m)}{(f_{max}-f_{avg})}, \qquad f_m \geq f_{avg} \tag{4.21a}$$

$$\Omega_m = 0.5 * \frac{(f_{max}-f_m)}{(f_{avg}-f_{min})}, \qquad f_m < f_{avg} \tag{4.21b}$$

Where, f_{max}, f_{avg} and f_{min} are the maximum, average and minimum fitness value of the population. f_c is the lower of the fitness value of the individuals to be crossed, and f_m is the fitness value of the mutating individuals.

GA#5: Chaogai Xue, Lili Dong and Junjuan Liu [80] proposed an adaptive approaches for crossover and mutation operator of the GA are as follows:

$$\Omega_c = \Omega_{c1} - \frac{(\Omega_{c1}-\Omega_{c2}) * (f_c-f_{avg})}{(f_{max}-f_{avg})}, \qquad f_c \geq f_{avg} \tag{4.22a}$$

$$\Omega_c = \Omega_{c1}, \qquad f_c < f_{avg} \tag{4.22b}$$

$$\Omega_m = \Omega_{m1} - \frac{(\Omega_{m1} - \Omega_{m2}) * (f_c - f_{avg})}{(f_{max} - f_{avg})} \quad , \quad f_m \geq f_{avg} \tag{4.23a}$$

$$\Omega_m = \Omega_{m1} \quad , \quad f_m < f_{avg} \tag{4.23b}$$

Where, f_{max} , f_{avg} and f_{min} are the maximum, average and minimum fitness value of the population. f_c is the grater of the fitness value of the two individuals to be crossed, and f_m is the fitness value of the mutating individuals, pC_1, pC_2 and pM_1, pM_2 are initial values for calculating self-adaptive crossover and mutation probability respectively.

GA#7: combination of two different IGA approach. Adaptive crossover operator taken from [76] and adaptive mutation operator taken from [79].

GA#8: combination of two different IGA approach. Adaptive crossover operator taken from [76] and adaptive mutation operator taken from [77].

4.7.1 Algorithm of Adaptive GA

The algorithm of all adaptive genetic algorithm is same with the basic genetic algorithm. In basic genetic algorithm the crossover and mutation GA parameters are initialize at the starting of the program. But in the adaptive genetic algorithm the crossover and mutation parameter are updated in every generation before the crossover and mutation is performed. Because the parameter are adaptive in nature. The flowchart for the adaptive genetic algorithm is presented below.

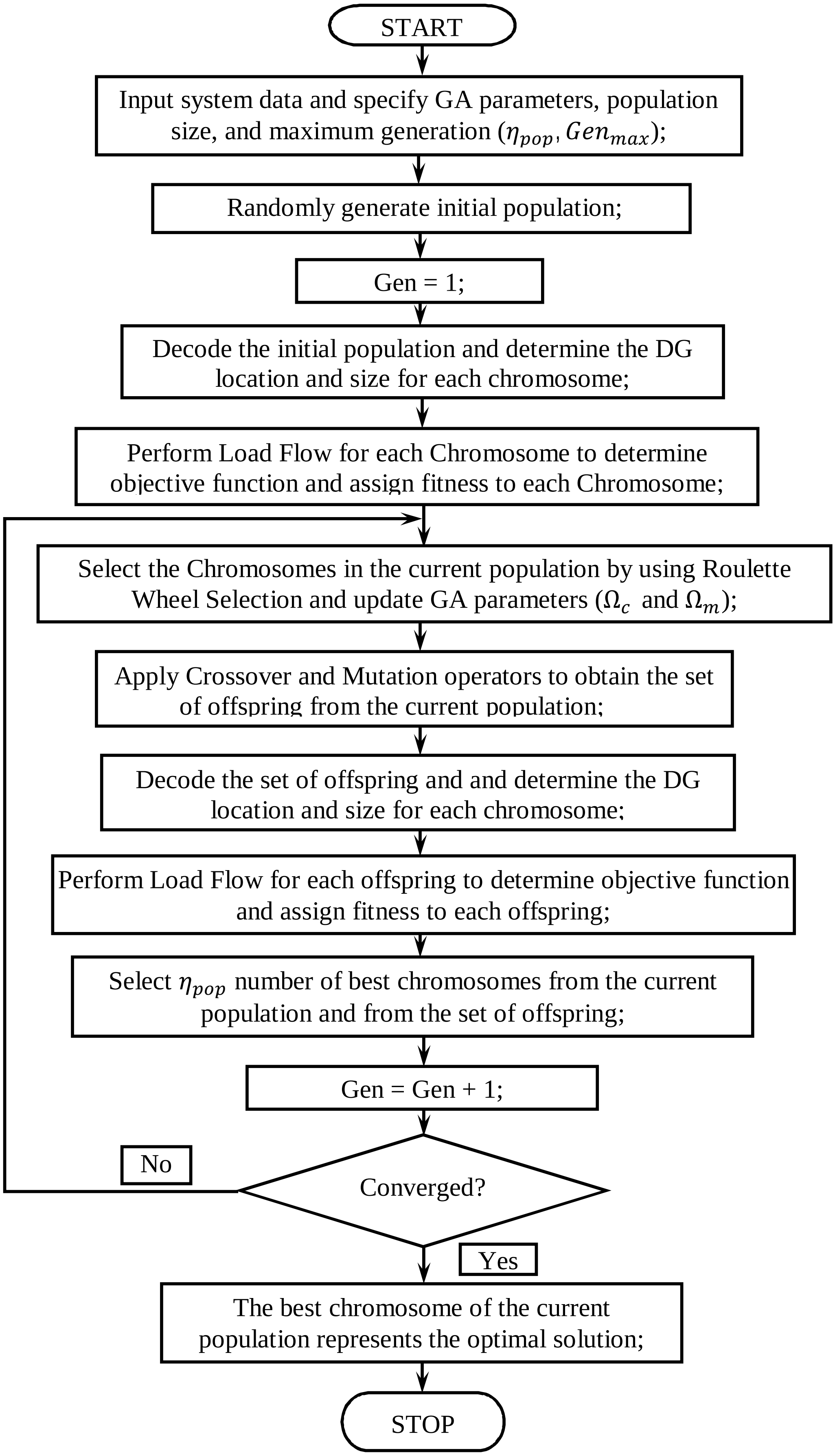


Figure 4.18. Flowchart of adaptive genetic algorithm for DG allocations

4.8 CASE STUDY FOR ADAPTIVE GA OPTIMIZATION

Table 4.12. Comparison of various GA optimization for DG allocation with system#1

Sl. No.	Type of Genetic Algorithm	Minimum Active Power Loss (kW)			Average Active Power Loss (kW)		Minimum Voltage		
		Elite	Mean Value	Standard Deviation	Mean Value	Standard Deviation	Minimum Value	Mean Value	Standard Deviation
1	Basic GA	49.86	55.131	4.8275	56.709	5.3512	0.96948	0.97423	0.0042605
2	GA # 1	49.779	58.078	5.5018	58.078	5.5018	0.96955	0.97592	0.0042795
3	GA # 2	48.001	53.289	4.4681	69.598	4.5672	0.96957	0.97631	0.0039185
4	*GA # 3*	*50.083*	*54.701*	*4.4502*	*55.221*	*4.6808*	*0.96776*	*0.97190*	*0.0033094*
5	GA # 4	50.409	76.082	20.646	120.46	56.762	0.92805	0.95856	0.019387
6	GA # 5	49.784	56.69	5.4992	59.183	6.8042	0.96784	0.97506	0.0045321
7	***GA # 6***	***50.130***	***54.884***	***4.3212***	***56.453***	***4.8723***	***0.96776***	***0.97322***	***0.0043029***
8	GA # 7	49.818	58.121	5.1599	58.121	5.1599	0.96957	0.97617	0.0042090
9	GA # 8	49.755	58.822	5.1633	58.822	5.1633	0.96956	0.97637	0.0039306

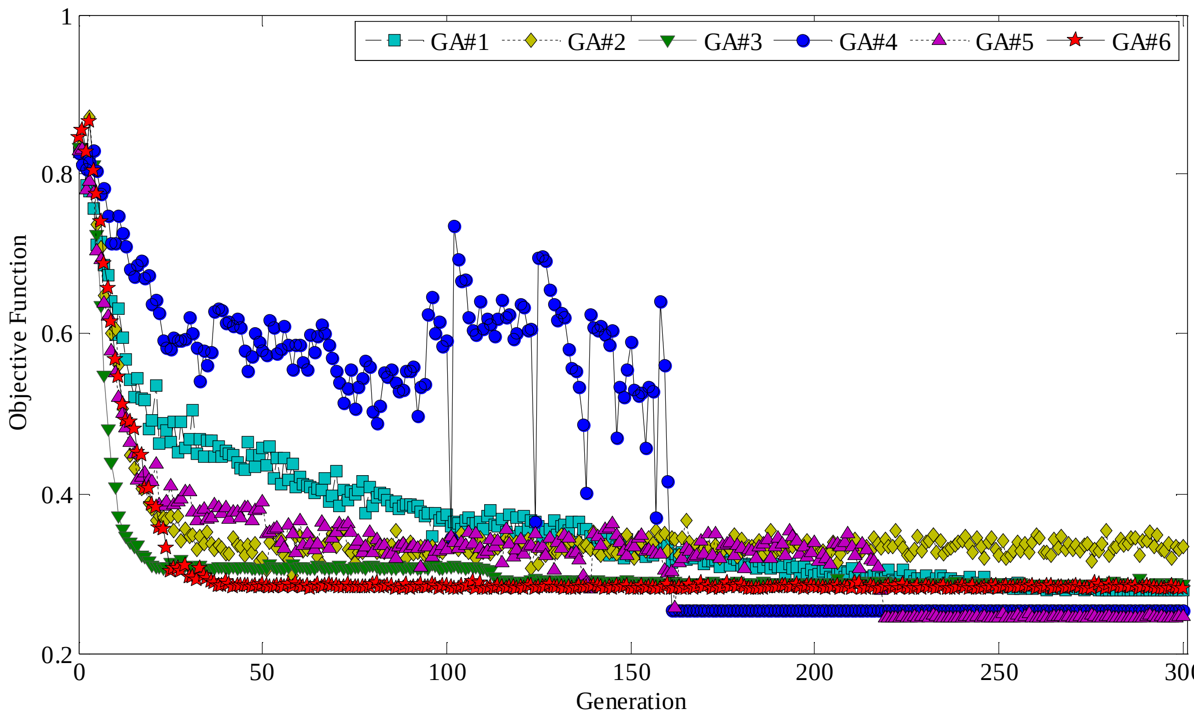


Figure 4.19. Average objective function of different GA for System#1

The Table 4.12 and Figure 4.19 shows the results of various adaptive GA optimization approaches. In this case study only case#1(a) is considered (i.e. installed DG are operated at unity p.f. on the distribution systems). All the GA a give a well constricted result. But, some of the GA give more satisfactory results (i.e. less standard dilation, low minimum power loss in the generations, high minimum node voltage compare to other, etc.). The second objective function gives the better performance with all the adaptive GA and particularly with basic GA compare to first objective function approach. Though the basic GA have a quick convergence criteria. Results shows that GA#3 have the best result among all of the GA previously proposed by others though the GA is partially adaptive in nature. Table 4.12 is also contained the proposed adaptive genetic algorithm results. It shows that the proposed adaptive GA gives the most satisfactory and acceptable result among all the GA approach is considered in the study. The proposed GA give the better result in all part of optimization (i.e. in case for minimum voltage and power loss). The optimized result of GA#3 are discussed briefly in the section 4.8.1 and proposed GA are discussed letter stage of this thesis.

4.8.1 Case Study for Adaptive Ga#3 Optimization

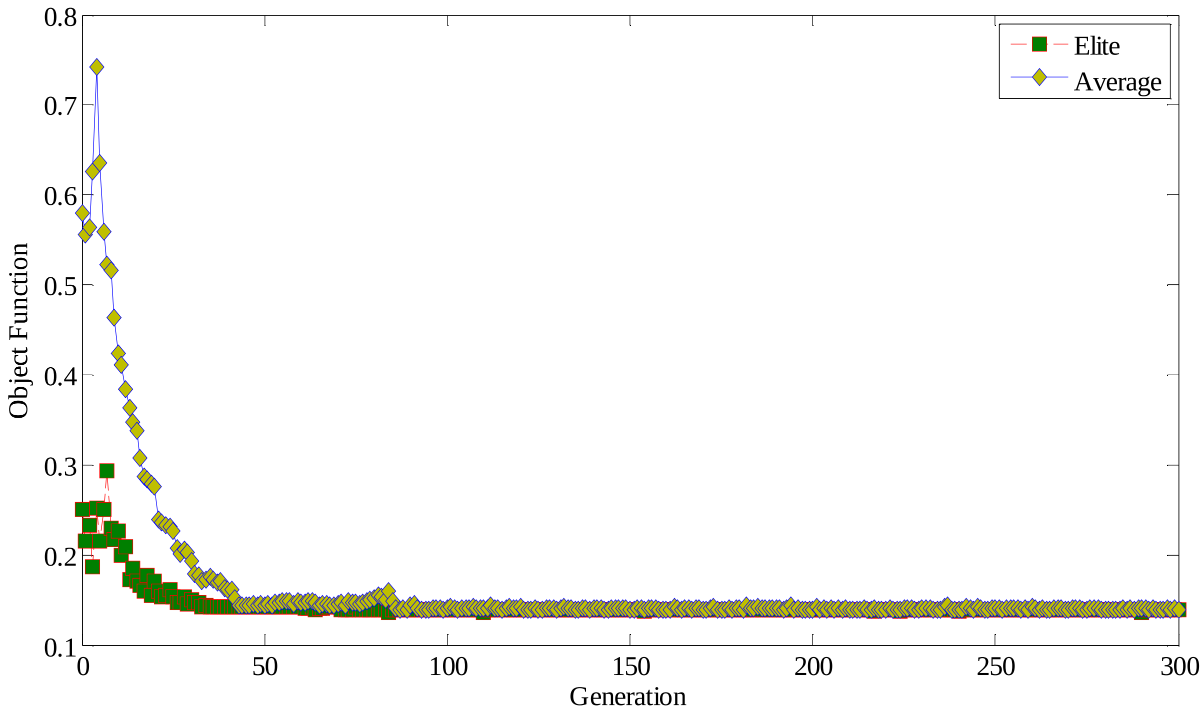


Figure 4.20. Convergence of GA#3 for unity p.f. DG optimization with System#1

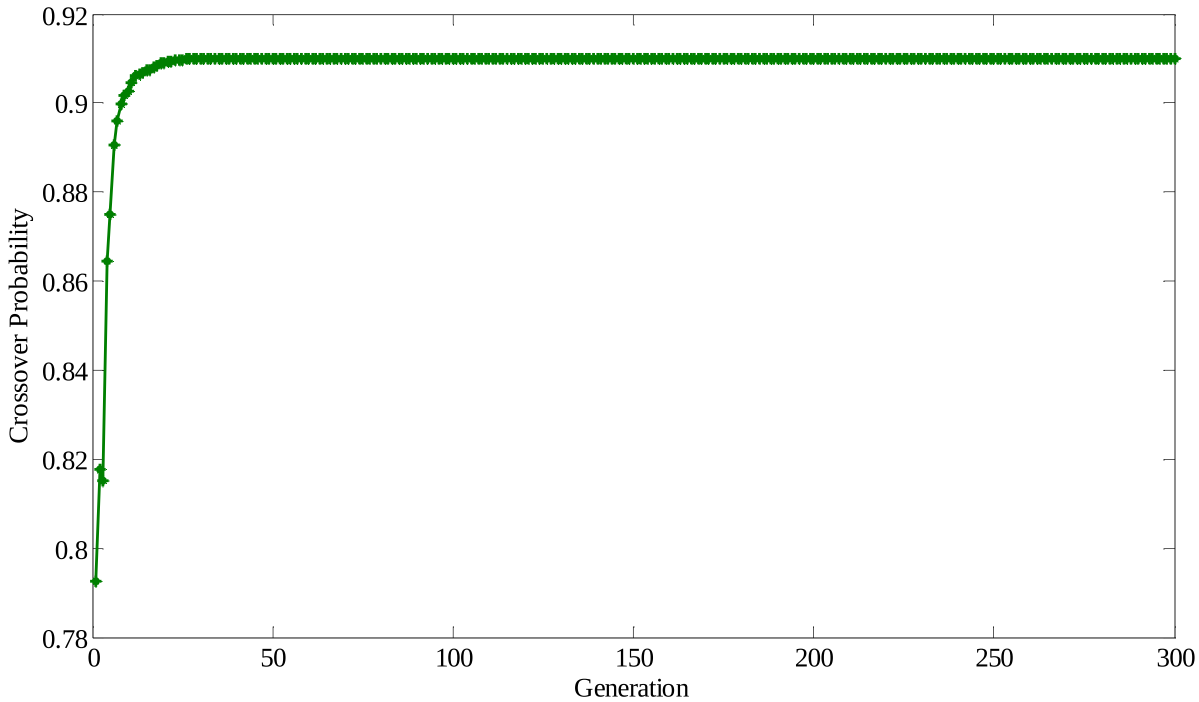


Figure 4.21. Adaptive crossover probability of GA#3 with System#2

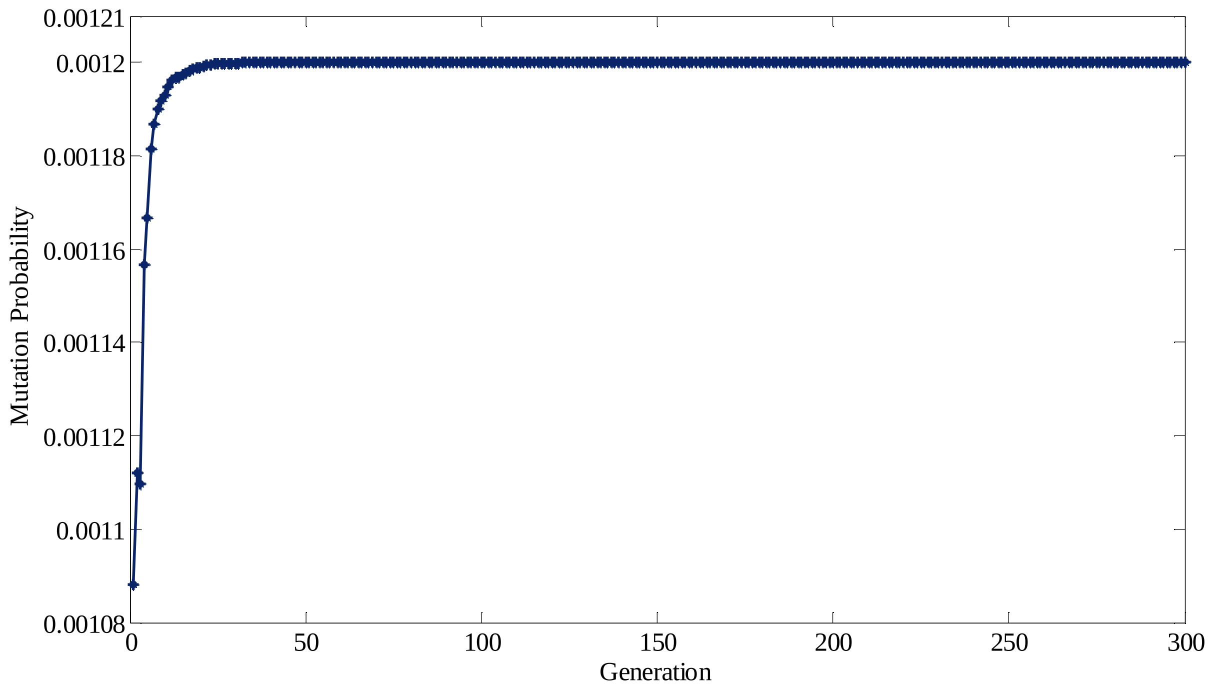


Figure 4.22. Adaptive mutation probability of GA#3 with System#2

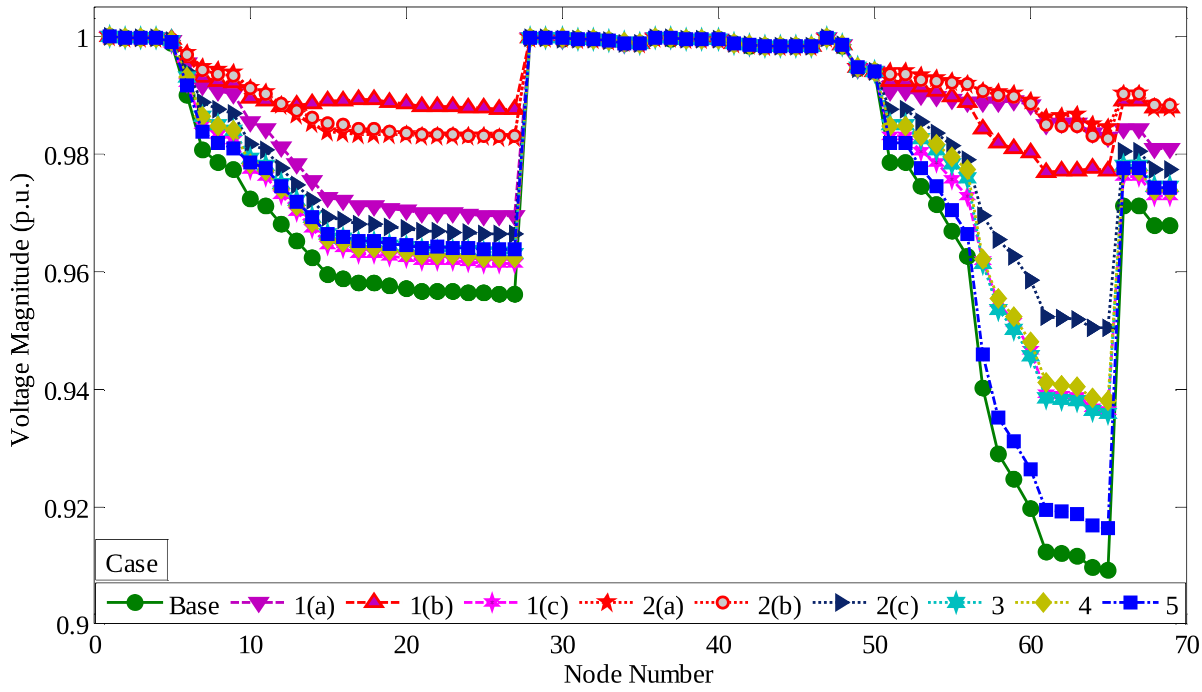


Figure 4.23. Node voltage magnitude of GA#3 for system#1 in different cases;

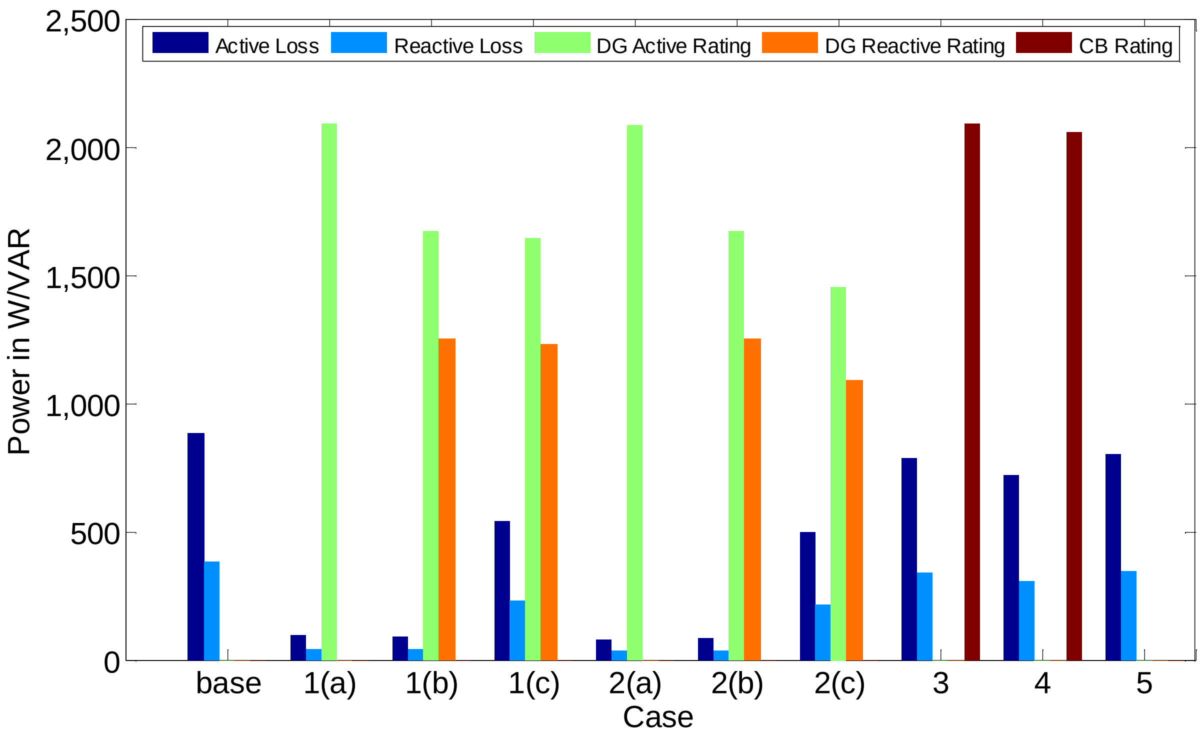


Figure 4.24. Active and Reactive power loss with injected DG and capacitor bank power rating.

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

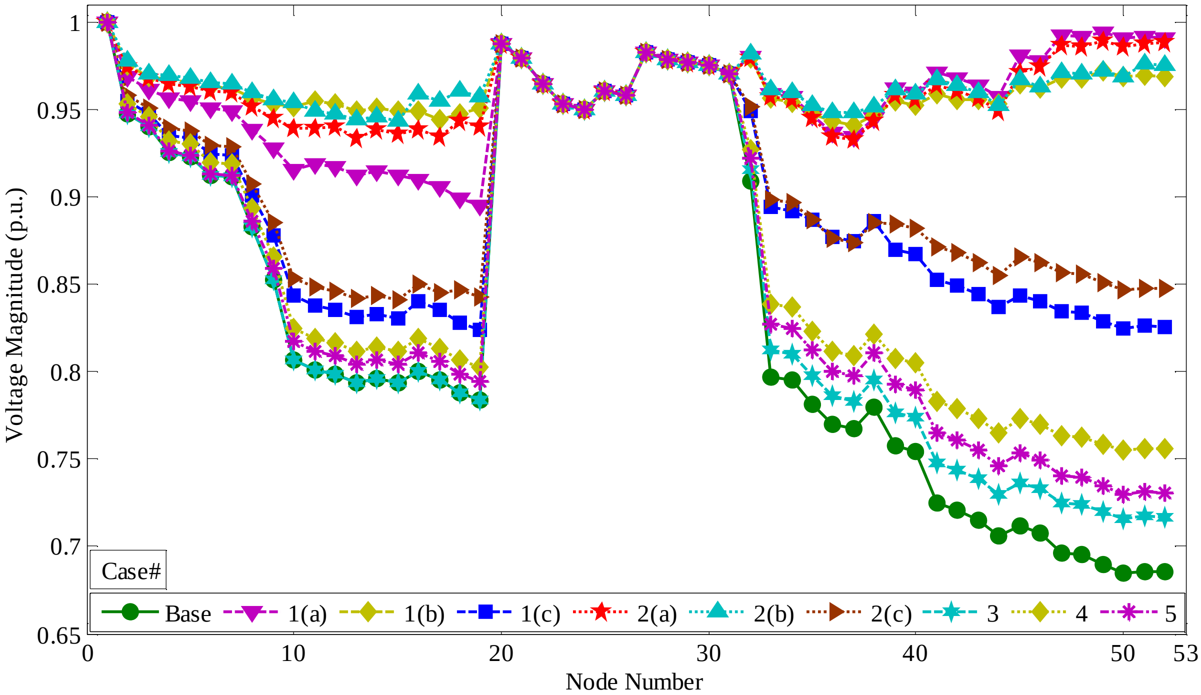


Figure 4.25. Node voltage magnitude of GA#3 for System#2

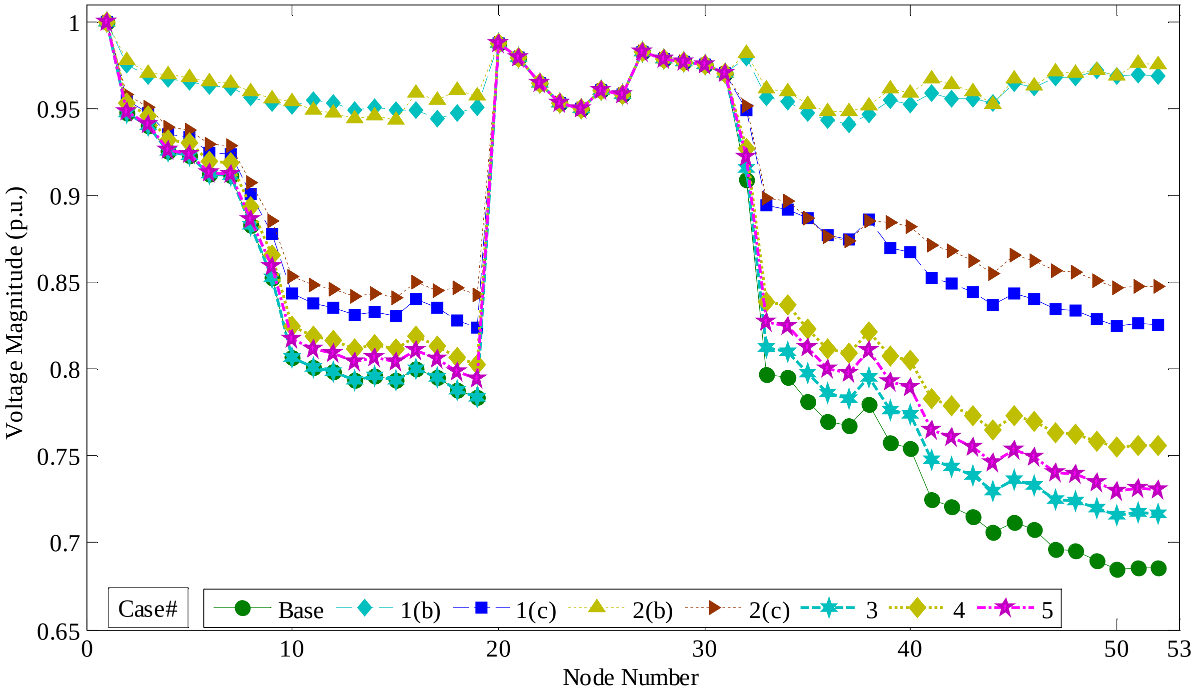


Figure 4.26. Node voltage magnitude of GA#3 for System#2;

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

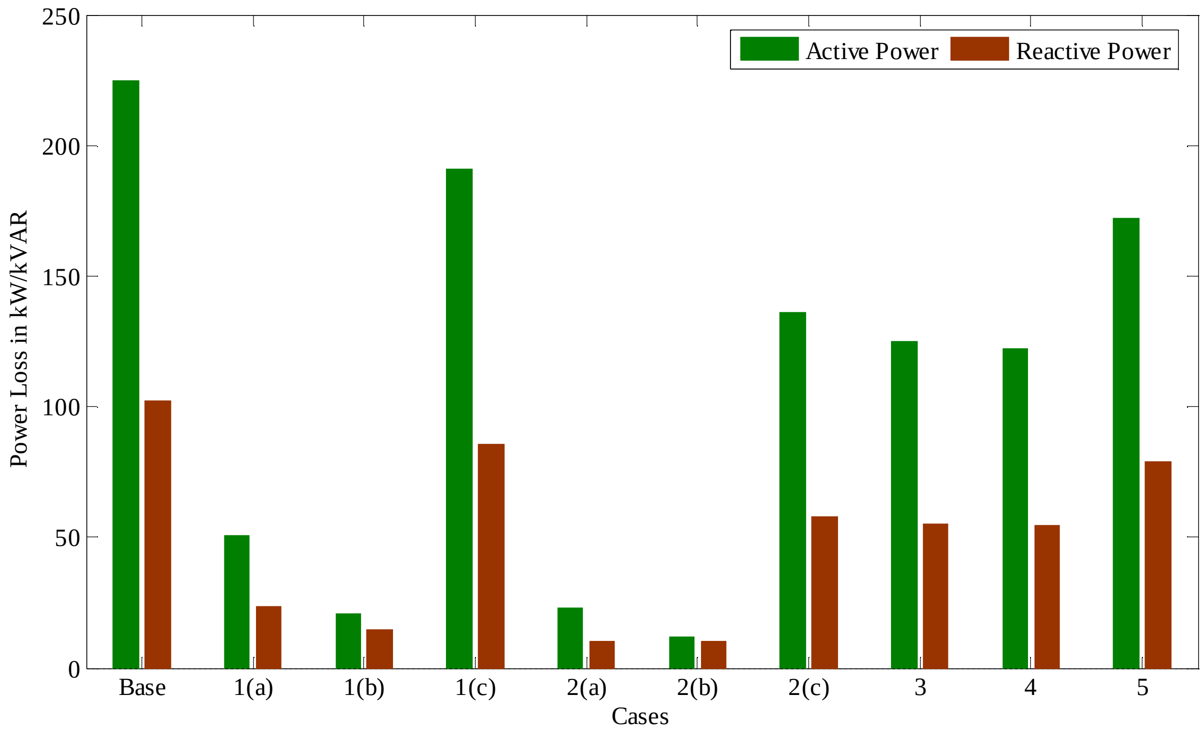


Figure 4.27. Variation of optimal active and reactive power loss of system#1 in different cases;

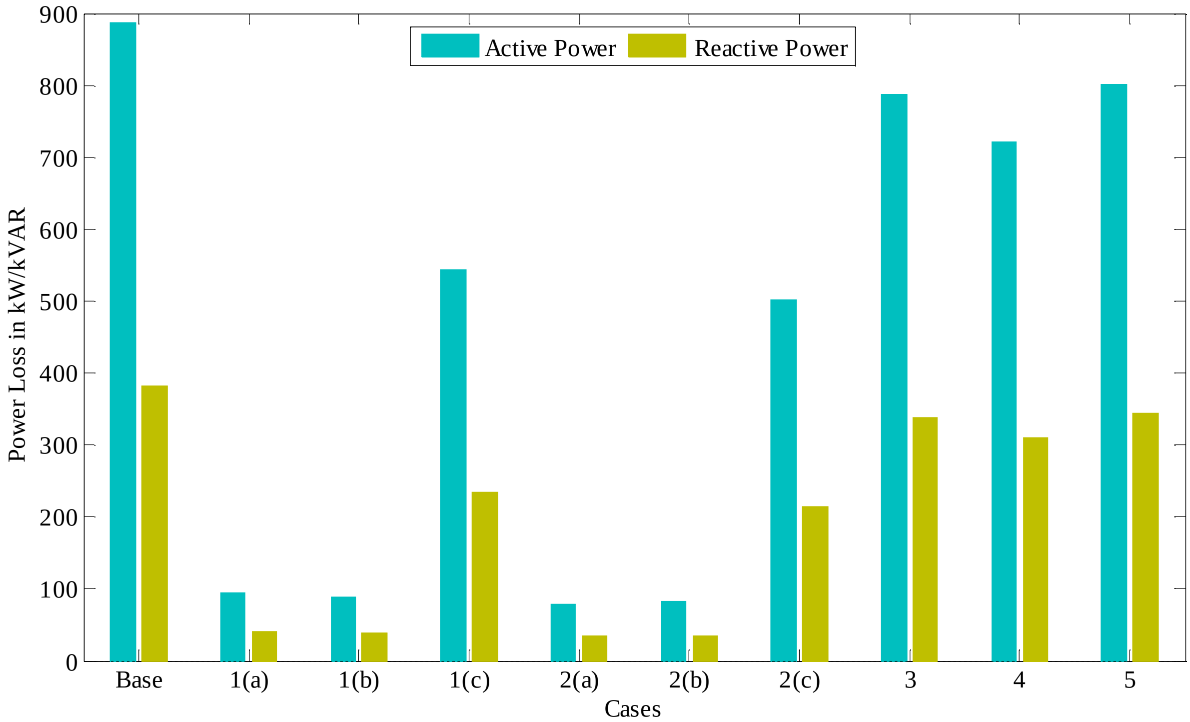


Figure 4.28. Variation of optimal active and reactive power loss of system#2 in different cases;

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

Table 4.13. Different case study for different system with GA#3 optimization

Different Cases	Different systems	No. of DG	Total DG Power Active Power (kW)	Total DG Power Active Power (kW)	No. of Tap	No. of CB	Total CB Reactive Power (kVAR)	Optimal Active Power Loss (kW)	Optimal Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
Base	System # 1	-	-	-	-	-	-	224.995	102.198	0.90919	0.49031
	System # 2	-	-	-	-	-	-	887.181	381.694	0.68442	2.43820
Case # 1 (a)	System # 1	4	2094.0	-	-	-	-	50.978	23.547	0.96958	0.32700
	System # 2	4	2094.0	-	-	-	-	93.850	40.377	0.89538	1.30910
Case # 1 (b)	System # 1	4	1659.2	1244.4	-	-	-	20.710	14.538	0.97706	0.26130
	System # 2	6	1674.4	1255.8	-	-	-	89.718	38.599	0.94084	1.30910
Case # 1 (c)	System # 1	3	1438.4	-1078.8	-	-	-	190.849	85.898	0.93630	0.46620
	System # 2	5	1648.0	-1236.0	-	-	-	544.027	234.058	0.82427	2.09880
Case # 2 (a)	System # 1	5	2085.0	-	9	-	-	23.267	10.286	0.98302	0.23862
	System # 2	6	2091.0	-	20	-	-	78.929	33.957	0.93245	1.30910
Case # 2 (b)	System # 1	5	1678.4	1258.8	10	-	-	11.974	10.253	0.98277	0.23927
	System # 2	6	1676.8	1257.6	19	-	-	82.762	35.607	0.94343	1.30910
Case # 2 (c)	System # 1	5	1629.6	-1222.2	10	-	-	135.960	57.730	0.95038	0.36630
	System # 2	6	1459.2	-1094.4	19	-	-	500.888	215.498	0.84141	1.93830
Case # 3	System # 1	-	-	-	-	5	2082	125.206	55.427	0.93581	0.40294
	System # 2	-	-	-	-	4	2095	787.116	338.643	0.71616	2.25750
Case # 4	System # 1	-	-	-	9	3	1775	122.123	54.421	0.93815	0.40351
	System # 2	-	-	-	20	4	2063	720.744	310.088	0.75501	2.13290
Case # 5	System # 1	-	-	-	10	-	-	172.001	78.965	0.91645	0.43333
	System # 2	-	-	-	19	-	-	802.015	345.053	0.72977	2.27660

Table 4.14. Position and rating for DG and CB of GA#3 optimization in different cases

Different System	DG rating kW						Capacitor bank rating kVAR	
	Case # 1(a)	*Case # 1(b)*	*Case # 1(c)*	*Case # 2(a)*	*Case # 2(b)*	*Case # 2(c)*	*Case # 3*	*Case # 4*
System # 1	DG_{59} = 447	DG_{18} = 472	DG_{57} = 598	DG_{21} = 177	DG_{16} = 176	DG_{58} = 567	CB_{57} = 394	CB_{58} = 591
	DG_{60} = 533	DG_{60} = 576	DG_{58} = 600	DG_{59} = 586	DG_{59} = 492	DG_{59} = 589	CB_{58} = 542	CB_{59} = 588
	DG_{61} = 596	DG_{61} = 564	DG_{59} = 600	DG_{61} = 529	DG_{60} = 558	DG_{60} = 581	CB_{59} = 585	CB_{60} = 596
	DG_{63} = 518	DG_{64} = 462	-	DG_{62} = 307	DG_{61} = 600	DG_{63} = 170	CB_{60} = 594	-
	-	-	-	DG_{63} = 486	DG_{63} = 272	DG_{65} = 130	CB_{64} = 067	-
System # 2	DG_{11} = 596	DG_{11} = 594	DG_{16} = 352	DG_{12} = 375	DG_{16} = 509	DG_{18} = 316	CB_{49} = 503	CB_{47} = 589
	DG_{45} = 465	DG_{19} = 180	DG_{33} = 598	DG_{18} = 350	DG_{18} = 239	DG_{35} = 104	CB_{50} = 543	CB_{50} = 567
	DG_{47} = 572	DG_{36} = 126	DG_{35} = 372	DG_{46} = 206	DG_{37} = 121	DG_{39} = 426	CB_{51} = 599	CB_{51} = 424
	DG_{49} = 461	DG_{44} = 085	DG_{41} = 461	DG_{47} = 597	DG_{41} = 600	DG_{41} = 340	CB_{52} = 450	CB_{52} = 483
	-	DG_{45} = 508	DG_{47} = 277	DG_{49} = 502	DG_{47} = 236	DG_{51} = 391	-	-
	-	DG_{49} = 600	-	DG_{52} = 079	DG_{51} = 391	DG_{45} = 417	-	-
	-	-	-	-	-	DG_{47} = 221	-	-

4.9 PROPOSED ADAPTIVE GA OPTIMIZATION

According to the literature review in IGA, crossover and mutation are in adaptive in nature. In some cases either crossover or mutation is in adaptive nature. So in some case only crossover probability or mutation probability is adaptive where other one is fixed in nature. But in some cases both are adaptive. Basically in the most of the IGA, crossover and mutation probability is directly related to the fitness function of the population. It can be divided into two category. In the first category it depends upon the maximum and minimum fitness of the population. Due to this either crossover or mutation or both are in partial adaptive in nature for all population of a single generation (i.e. fixed for all matting chromosomes). Or we can say generation wise adaptive in nature. But when either crossover or mutation or both depends upon individual matting chromosome pair fitness and maximum and minimum fitness of the population it become adaptive in nature for all population of a single generation (i.e. different for all matting chromosomes). Thus in this second category, crossover and mutation is not only generation wise also population wise adaptive in nature.

By considering all the concept the proposed adaptive GA is based on second category where only crossover probability is adaptive in nature and which is used for optimal DG allocation and size problem. The adaptive crossover probability is directly depends upon the present generation maximum and minimum fitness and the matting chromosome fitness. This adaptive crossover probability is mathematically formulated as follows:

$$\Omega_c = f_{max} - (f_{max} - f_c) * e^{\left(\frac{f_{max} - f_{min}}{n_c}\right)}, \qquad f_c \geq f_{avg} \tag{4.24a}$$

$$\Omega_c = f_{max} - \left(f_{avg} - f_c\right) * e^{\left(\frac{f_{avg} - f_{min}}{n_c}\right)}, \qquad f_c < f_{avg} \tag{4.24b}$$

Where, f_{max} , f_{avg} and f_{min} are the maximum, average and minimum fitness value of the population. f_c is the grater of the fitness value of the two individuals to be crossed, n_c is coefficient factor.

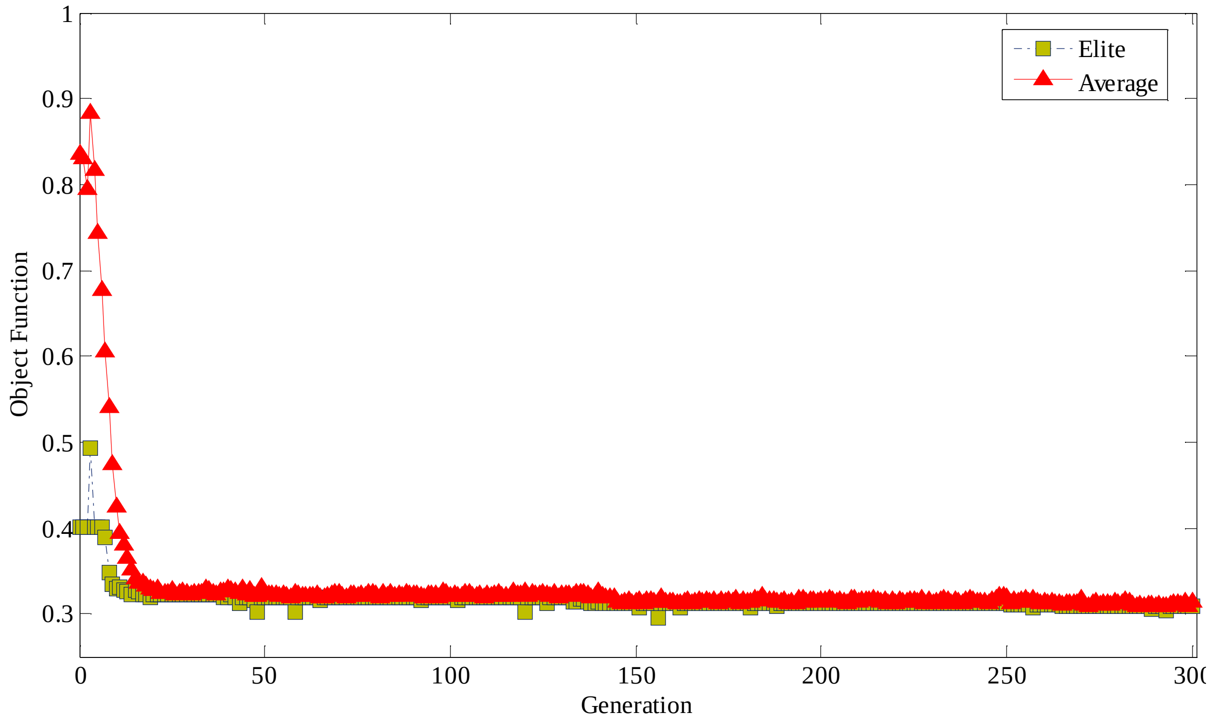


Figure 4.29. Convergence of GA#6 for unity p.f. DG optimization with System#1

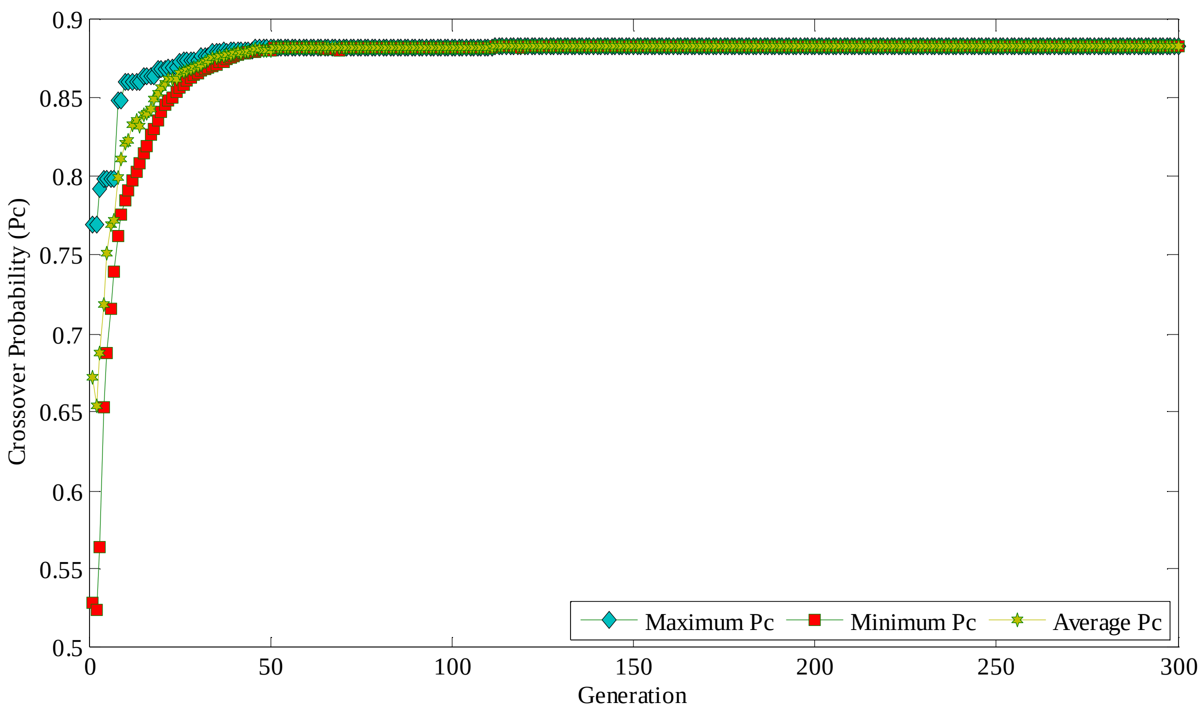


Figure 4.30. Adaptive crossover probability of GA#6 with System#2

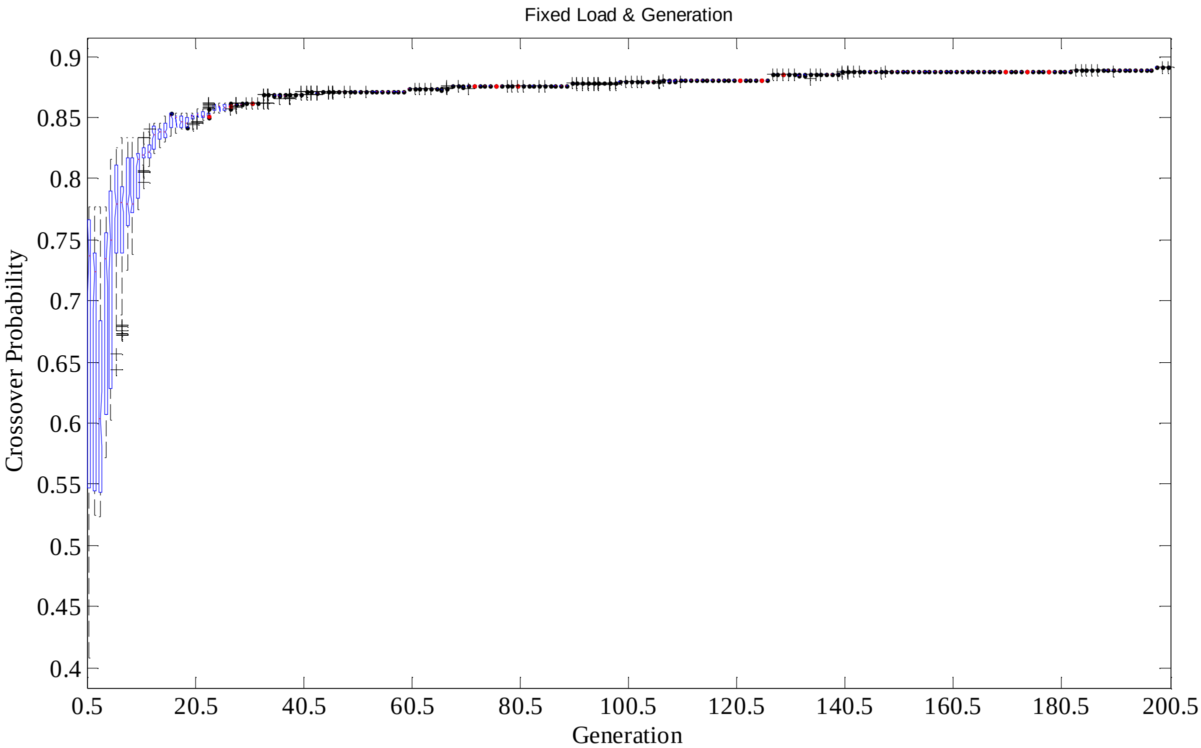


Figure 4.31. Variation of adaptive crossover probability of GA#6 in each and every generation with System#2

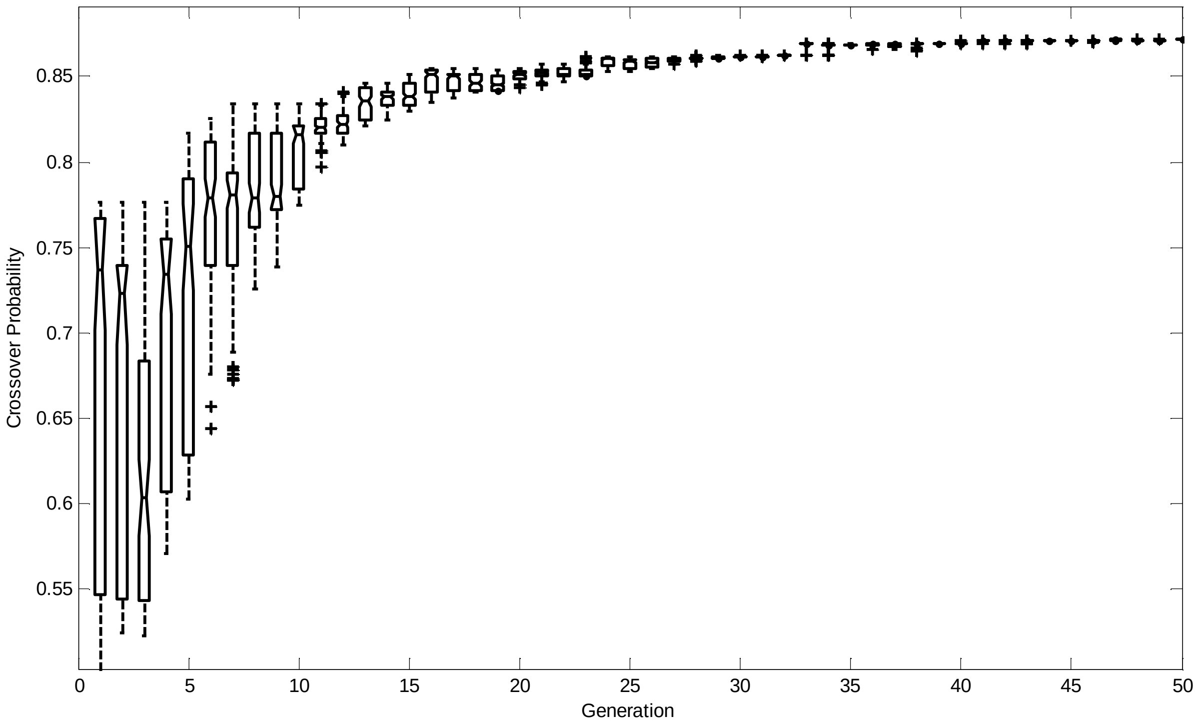


Figure 4.32. Zooming up the adaptive crossover probability of GA#6 up to generation 50

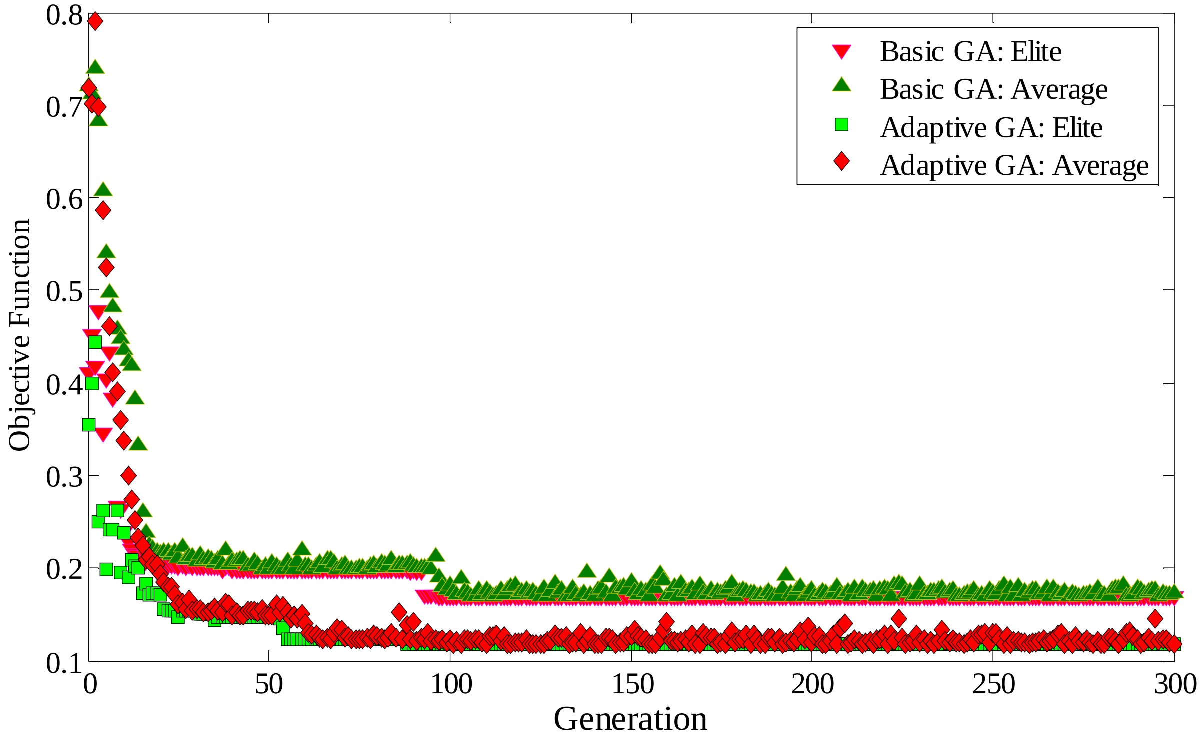


Figure 4.33. Compression between basic GA and proposed adaptive GA optimization for unity p.f. DG with system#2

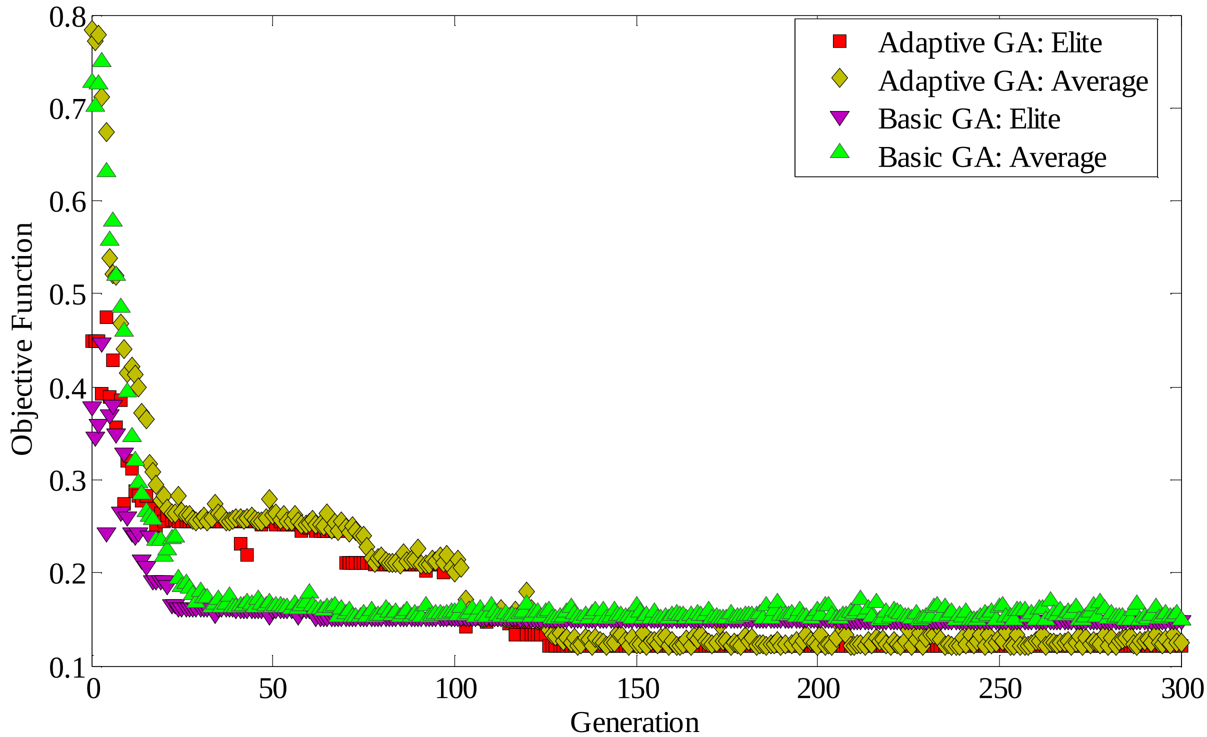


Figure 4.34. Compression between basic GA and proposed adaptive GA optimization for 0.8 p.f. DG supplying reactive power with system#2

Table 4.15. Different case study for different system with GA#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power Active Power (kW)	Total DG Power Reactive Power (kVAR)	No. of Tap	No. of CB	Total CB Reactive Power (kW)	Optimal Active Power Loss (kW)	Optimal Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
Base	*System # 1*	-	-	-	-	-	-	224.995	102.198	0.90919	0.49031
	System # 2	-	-	-	-	-	-	887.181	381.694	0.68442	2.43820
Case # 1 (a)	*System # 1*	4	2088.0	-	-	-	-	50.557	24.0396	0.96953	0.32060
	System # 2	5	2095.0	-	-	-	-	92.600	39.839	0.92560	1.30910
Case # 1 (b)	*System # 1*	5	1678.4	1258.8	-	-	-	17.624	13.135	0.98035	0.25856
	System # 2	6	1679.2	1259.4	-	-	-	89.619	38.557	0.93813	1.30910
Case # 1 (c)	*System # 1*	3	1433.6	-1075.6	-	-	-	190.731	85.864	0.93621	0.46614
	System # 2	4	1650.4	-1237.8	-	-	-	535.504	230.391	0.82221	2.11770
Case # 2 (a)	*System # 1*	5	2087.0	-	8	-	-	16.598	9.694	0.97902	0.23973
	System # 2	6	2095.0	-	19	-	-	77.164	33.059	0.93456	1.30910
Case # 2 (b)	*System # 1*	5	1676.0	1257.0	9	-	-	7.698	4.534	0.98803	0.21735
	System # 2	6	1678.4	1258.8	20	-	-	76.789	33.037	0.95106	1.30830
Case # 2 (c)	*System # 1*	4	1634.4	-1225.8	10	-	-	128.582	56.112	0.95070	0.36631
	System # 2	4	1658.4	-1243.8	20	-	-	483.191	207.885	0.84036	1.91430
Case # 3	*System # 1*	-	-	-	-	4	2099	128.676	57.0404	0.93814	0.40236
	System # 2	-	-	-	-	4	2096	786.995	338.591	0.71626	2.25760
Case # 4	*System # 1*	-	-	-	7	4	2091	120.470	56.114	0.94519	0.39981
	System # 2	-	-	-	20	4	2090	716.607	308.308	0.75746	2.12410
Case # 5	*System # 1*	-	-	-	10	-	-	169.244	77.768	0.91721	0.43167
	System # 2	-	-	-	20	-	-	796.285	342.588	0.73196	2.26360

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

After analysing the above results, it can be summarised that effectively the proposed adaptive GA give better results. The convergence criteria of the proposed adaptive GA is well acceptable. Figure 4.31 and Figure 4.32 shows that the crossover probability is fully adaptive in nature (i.e. it is not only generation wise also population wise adaptive in nature). The proposed AGA is tested on both the systems for the all case considered in the study and satisfactory results are achieved in all cases. The quick convergence of GA and stuck in a local minima can be avoided by this adaptive crossover approach.

4.10 CASE STUDY FOR SELECTION OF UNCROSSED PARENTS

The offspring can be selected by two different method (i) best fitness parent among the parent pair and (ii) the chromosome belongs the same location or number of the selected parent's pair location or number in the population and matting pool respectively. The study is carried on the system#2 with GA#6 and the results are shown in the Table 4.16 below.

Table 4.16. Comparison of various uncrossed parents selection approach of GA optimization for dg allocation

Case	Type of Approach	Minimum Active Power Loss (kW)			Average Active Power Loss (kW)		Minimum Voltage			Average Objective Function	
		Elite	Mean Value	Standard Deviation	Mean Value	Standard Deviation	Minimum Value	Mean Value	Standard Deviation	Mean Value	Standard Deviation
1(a)	First	50.913	66.426	9.165	72.702	8.548	0.93370	0.94500	0.00450	0.12190	0.00540
	Second	45.649	59.642	9.319	65.573	10.720	0.93040	0.93930	0.00450	0.13690	0.00640
1(b)	First	62.980	65.120	1.291	68.091	2.366	0.95000	0.95150	0.00190	0.11910	0.00360
	Second	64.601	68.152	2.737	70.879	3.122	0.94130	0.94980	0.00220	0.12330	0.00490
1(c)	First	474.75	536.77	22.844	561.35	13.756	0.82425	0.83348	0.00486	0.58249	0.00505
	Second	484.04	540.28	21.109	559.18	15.663	0.78370	0.83064	0.01094	0.58352	0.01514
2(a)	First	38.139	50.454	8.756	54.828	8.864	0.94301	0.94979	0.00403	0.11443	0.00410
	Second	41.652	51.656	7.357	56.233	7.688	0.94124	0.94846	0.00391	0.11709	0.00593
2(b)	First	50.191	53.987	1.875	57.001	2.794	0.95362	0.95581	0.00268	0.10053	0.00377
	Second	52.423	56.212	2.222	59.661	2.778	0.95300	0.95490	0.00230	0.10980	0.00480
2(c)	First	441.61	483.60	16.922	504.74	12.403	0.82323	0.84981	0.00698	0.52509	0.00817
	Second	422.68	471.94	24.719	495.53	21.399	0.82810	0.84880	0.00770	0.52120	0.01160
3	First	778.25	778.58	0.1906	779.26	0.5583	0.71840	0.71890	0.00020	0.88520	0.00070
	Second	778.31	778.68	0.2119	779.35	0.5547	0.71820	0.71880	0.00020	0.88540	0.00070
4	First	708.69	713.04	2.099	714.54	2.157	0.77970	0.78430	0.00080	0.78630	0.00250
	Second	708.10	712.91	2.643	714.51	2.667	0.75630	0.75870	0.00100	0.78640	0.00310
5	First	792.09	797.21	3.284	798.57	3.441	0.72980	0.73100	0.00080	0.87730	0.00320
	Second	792.50	796.18	2.046	797.62	2.146	0.73033	0.73130	0.00052	0.87639	0.00202

case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

After analysing the above results, it can be summarised that the first approach is better than second (i.e. when the crossover criteria is not satisfied then the offspring will bear only chromosome belongs the same location or number of the selected parent’s pair location or number in the population and matting pool respectively). These selection give better voltage profile and low power losses in almost all cases except the case#5 in which only OLTC is controlling the voltage and minimizing the power losses.

4.11 SUMMARY

In this chapter, a deterministic method to find the optimal DG sizing and placement in a distribution network was proposed, where the total real power loss of the network were employed as the objective to be minimised. Both the single-objective and multi-objective optimization method was employed for DG allocation issue. After analysing the above results, it can be summarised that DG placement in the distribution system is profitable. DG not only minimised the power loss of the distribution system also it improved the voltage profile. The multi-objective optimization give the better optimal result then the single-objective optimization. All the adaptive GA gives a well constricted result. But, some of the GA give more satisfactory results (i.e. less standard dilation, low minimum power loss in the generations, high minimum node voltage compare to other, etc.). The second objective function approach gives the better performance with all the adaptive GA and particularly with basic GA compare to first objective function approach. Though the basic GA have a quick convergence criteria it can provide considerable optimal results. Results shows that GA#3 have the best result among all of the GA previously proposed by others though the GA is partially adaptive in nature. The proposed adaptive GA gives the most satisfactory and acceptable result among all the GA approach is considered in the study. The proposed GA give the better result in all part of optimization (i.e. in case for minimum voltage and power loss).

The convergence criteria of the proposed adaptive GA is well acceptable. The crossover probability of proposed GA is fully adaptive in nature (i.e. it is not only generation wise also population wise adaptive in nature). The quick convergence of GA and stuck in a local minima can be avoided by this adaptive crossover approach. Synchronous DG are profitable application in all type of system also induction DG are considerable profitable though they consumed reactive power from the system. Installation of induction DG in a very week distribution system is better than the capacitor placement.

CHAPTER-5

OPTIMAL DG ALLOCATION UNDER VARIABLE LOAD AND GENERATION USING GENETIC ALGORITHM

5.1 INTRODUCTION

Distributed generation (DG) technologies under smart grid concept forms the backbone of our world Electric distribution networks [5]. These DG technologies are classified into two categories: (i) renewable energy sources (RES) and (ii) fossil fuel-based sources. Renewable energy source (RES) based DGs are wind turbines, photovoltaic, biomass, geothermal, small hydro, etc. Fossil fuel based DGs are the internal combustion engines (IC), combustion turbines and fuel cells. Environmental, economic and technical factors have a huge role in DG development [3] [6-7]. In accord with the Kyoto agreement on climate change, many efforts to reduce carbon emissions have been taken, and as a result of which, the penetration of DGs in distribution systems rises [8]. Presence of Distributed generation in distribution networks is a momentous challenge in terms of technical and safety issues [12–14]. Thus, it is critical to evaluate the technical impacts of DG in power networks. Thus, the generators are needed to be connected in distributed systems in such a manner that it avoids degradation of power quality and reliability. Evaluation of the technical impacts of DG in the power networks is very critical and laborious. Inadequate allocation of DG in terms of its location and capacity may lead to increase in fault currents, causes voltage variations, interfere in voltage-control processes, diminish or increase losses, increase system capital and operating costs, etc.[13].

The placement of the DG units mainly the Renewable energy sources placement, is affected by several factors such as wind speed, solar irradiation, environmental factors, geographical topography, political factors, etc. For example, wind generators or turbines cannot be installed near residential areas, because of the interference in the form of public reactions and legislations from environmental organisations. Another issue is application of the plug-in electric vehicle (PEV) which is being paid more attention to [44-46]. However, there are several factors or uncertainties that can possibly lead to probable risks in determining the optimal siting and sizing of DGs in distribution system planning [47]. Some of the uncertainties are possibilistic output power of a PEV due to its alteration of charging/discharging schedule [48-50], wind power unit due to frequent variable wind speed, from a solar generating source due to the possibilistic illumination intensity, volatile fuel prices and future uncertain load growth. The most essential uncertainty to account for the time-varying characteristics of both generation and demand of power are these increasing penetrations of variable renewable generators with wind power [47][53], being the most noteworthy of them.

5.2 MULTI-OBJECTIVE PLANNING OF RADIAL DISTRIBUTION NETWORKS USING PLGM

In most of the planning models, the optimal distribution network is determined based on a deterministic load demand which is usually obtained from a load forecast and DG generation. The optimal DG power generation of a distribution network is determined based on the DG generation (i.e., electric utilities and customers) and weather forecast in the form of wind or solar power generation. However, such a forecast is always subject to some error. Since the operating conditions (e.g. node voltage, branch current, illumination of sun, wind speed, etc.) of any distribution network depend on the load, a network operating with loads that differ from the nominal ones may be subject to violations of the acceptable operating conditions. In this study, load demand uncertainty (LDU) and DG power generation uncertainty (PGU) is incorporated into network planning to investigate its overall influence on planned networks. A possibilistic (fuzzy-based) approach can be used to model the uncertainty of LDU and PGU. Possibilistic approach, ambiguity of load demand and DG power generation can be modelled efficiently without any problem-specific knowledge. A fuzzy membership function can be used to model this inexplicit and uncertain information, providing degrees of membership to all possible values of the load demand and DG power generation for each and candidate node respectively.

5.2.1 Possibilistic Load and Generation Model (PLGM)

A fuzzy number is a special case of a convex, normalized fuzzy set representing an extension of real numbers. It is used to transform the verbal declaration of an uncertain number or an interval into its mathematical form. Fuzzy numbers allow the incorporation of uncertainty on parameters, properties, geometry, initial conditions, etc. A fuzzy number can be characterized by various mathematical functions [62, 63]. Load demand uncertainty (LDU) and DG power generation uncertainty (PGU) typically represented by triangular or trapezoidal fuzzy numbers [64], as shown in Figure 5.1 and Figure 5.3. In practice, the most probable load for each node of a distribution networks is forecasted by utility companies using it's high and low bounds. In this context, a triangular fuzzy number is a more practical way of translating this fuzzy information into an uncertainty range (an interval) plus an interior "most credible" value, which is obtained from the forecast [64]. Distributed generation is at present being used by customers to various purposes (i.e., to meet some or all of their electricity needs, to reduce demand charges by their electric utility, provide backup power, etc.). Also electric utilities are using their won controlled DG networks to enhance their distribution networks. Due to some electric utility controlled DG and customers uncontrolled DG, DG power generation uncertainty (PGU) typically represented by triangular fuzzy numbers. Thus, in this work, the load demand at each node and the DG power generation at candidate nodes are considered as a possibilistic variable represented by two different triangular fuzzy number. For load demand $\tilde{L} = (L_{d\_min}, L_{dr}, L_{d\_max})$ as shown in Figure 5.1, in which L_{d_min}, L_{dr} and L_{d_max} represent the minimum possible load demand, load demand with highest possibility of existence, and maximum possible load demand for a node, and for DG power generation $\tilde{P} = (P_{DG\_min}, P_{DGr}, P_{DG\_max})$ as shown in Figure 5.2, in which P_{DG_min}, P_{DGr} and P_{DG_max} represent the minimum possible DG power generation, DG power generation with highest possibility of existence, and maximum possible DG power generation for a candidate node. The objective functions is a function of load demand and DG power generation, which is also become possibilistic quantities (i.e., fuzzy numbers).

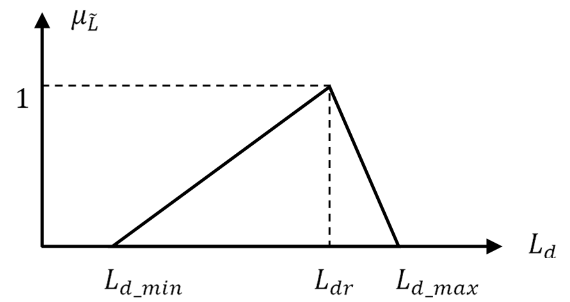


Figure 5.1. Possibilistic variable, i.e., possibilistic load demand, as a triangular fuzzy number,

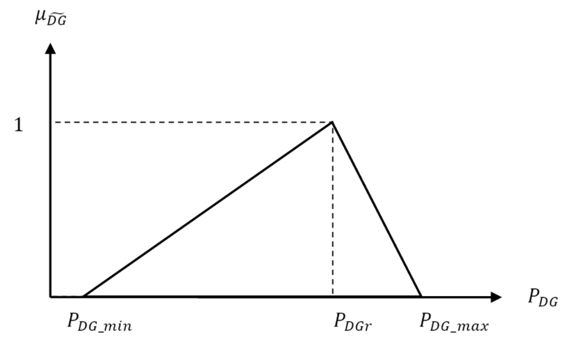


Figure 5.2 Possibilistic variable, i.e., possibilistic DG power generation, as a triangular fuzzy number,

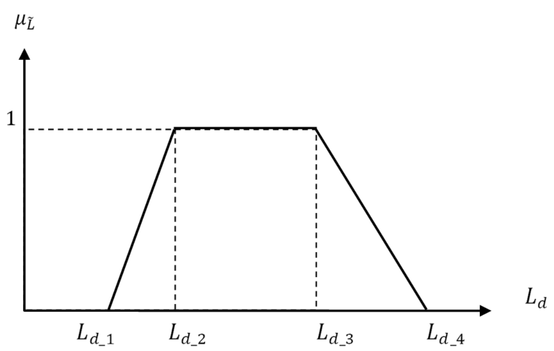


Figure 5.3. Fuzzy removal technique for a possibilistic objective function.

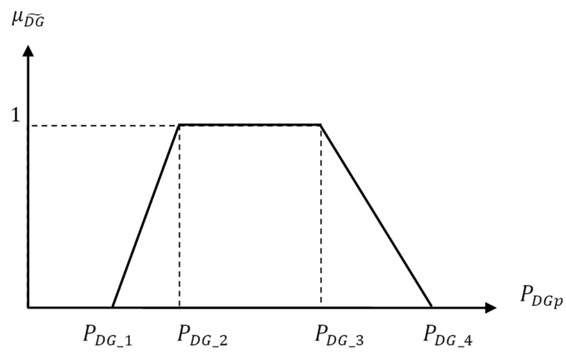


Figure 5.4. Fuzzy removal technique for a possibilistic objective function.

5.2.2 Comparison of Fuzzy Numbers

Fuzzy numbers forms the objective function for the optimization problem discussed in the study as a result of which direct comparison between two solutions is difficult. Hence, a suitable de-fuzzification approach is required of which a lot of literatures are available in [65-66]. The approach used in this study involves transforming of each index of the fuzzy quantities into real numbers where there is no need for a reference set or a fuzzy relation. In this case for de-fuzzification various approaches can be used (i.e., center of gravity (COG), mean of maxima (MOM), total distance criterion (TDC) index and fuzzy removal techniques) [67].COG ascribes relatively higher weights to lower membership values whereas MOM neglects lower membership values. TDC and removal techniques are basically equivalent [67]. The TDC or removal value is the average of the sum of areas under the left and right sides of the fuzzy membership function corresponding to an α-level. The method used in this study yields a reasonably good representation of a fuzzy set [53, 54]. In the present study, the removal technique was used to obtain equivalent crisp values of the fuzzy objective functions. For a triangular fuzzy number, the removal $\{Rem(\tilde{f})\}$ of a fuzzy objective function $(\tilde{f})$ corresponding to an α-cut is defined as (Ramirez-Rosado & Dominiguez-Navarra, 2004) (Figure 5.5):

$$Rem(\tilde{f}) = (f_{\alpha 1} + 2 * f_2 + f_{\alpha 2})/4 \quad (5.1)$$

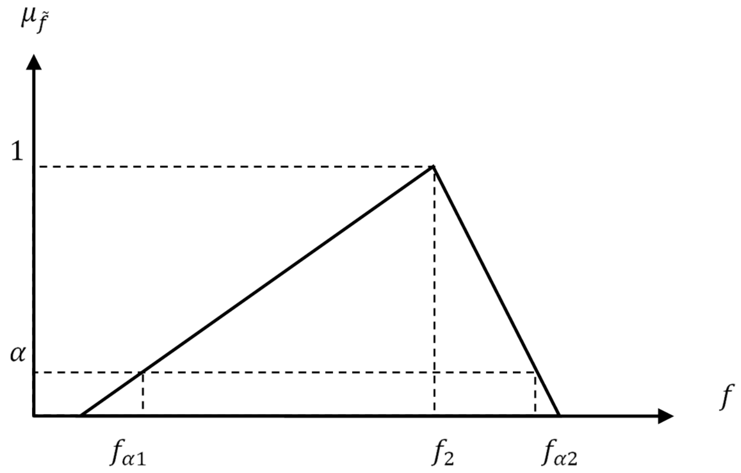


Figure 5.5. Fuzzy removal technique for a possibilistic objective function.

Two fuzzy numbers, $\tilde{a}$ and $\tilde{b}$, can be compared using their corresponding removal values $Rem(\tilde{a})$ and $Rem(\tilde{b})$. The value of α is user specific.

5.3 OBJECTIVE FUNCTIONS

A multi-objective optimization problem is consider in this distribution networks planning problem with continuous planning decision variables. The main objective is to determine an economical yet reliable network with better technical features, such as lower power loss, better node voltage profile, and better branch current/thermal limit ratio. Thus, two objective functions are formulated: minimization of (i) the total power loss (P_{loss}) of the distribution network and (ii) maximum node voltage deviation (V_{dev}) ratio. Optimization of (i) yields an economical and high efficient network and optimization of (ii) results in a reliable network with better technical features.

$$Rem(\tilde{f}_p) = \frac{\sum_i^{N_{Br}} \tilde{P}_{loss}^{with\_DG}}{\sum_i^{n_{Br}} \tilde{P}_{loss}^{without\_DG}} \qquad \forall i = N_{Br} \quad (5.2)$$

$$Rem(\tilde{f}_v) = \frac{max \quad (V_{sub} - \tilde{V}_i^{with\_DG})}{max \quad (V_{sub} - \tilde{V}_{base})} \tag{5.3}$$

The uncertain data are modelled as possibilistic quantities (triangular fuzzy numbers) using fuzzy set theory. Thus, the objective function also becomes a possibilistic quantity and the fuzzy α-removal approach is used to determine its equivalent crisp quantity. The objective is the minimization of the fuzzy removal of total power loss and maximum voltage deviation given below. Thus the total objective function become according to fuzzy removal representation:

$$Min \quad f = k_v Rem(\tilde{f}_v) + k_p Rem(\tilde{f}_p) \tag{5.4}$$

However, the distribution planning problem has three constraints: (i) node voltage constraint, (ii) branch thermal limit constraint and (iii) DG power rating constraint.

$$v^{min} \leq Rem(\tilde{v}_i) \leq v^{max} \qquad \forall i = N_B \tag{5.5}$$

$$Rem(\tilde{I}_i) \leq I_{i\_max} \qquad \forall i = N_{Br} \tag{5.6}$$

$$P_{DG}^{min} \leq Rem(\tilde{P}_{DG\_i}) \leq P_{DG}^{max} \qquad \forall i = N_B \tag{5.7}$$

Where, N_{Br} is the branch of the network, N_B is the node of the network, I_{i_max} and $\tilde{I}_i$ are the maximum branch current level and actual branch current, respectively.

5.4 DG ALLOCATION STRATEGY USING GA

A feeder brings power from substation to load points/nodes in radial distribution networks (RDN). Single or multiple radial feeders are used in this planning approach. Basically, the RDN total power losses can be minimized by minimizing the branch power flow or transported electrical power from transmission networks (i.e. some percentage of load are locally meeting by local DG). To determine the total power loss of the network or each feeder branch and the maximum voltage deviation are determined by performing load flow. The forward/backward sweep load flow technique is used in this case.

(A) Forward/Backward sweep load flow with DG

To study the impact of the DG allocation in distribution networks, the DG model is incorporated in the forward-backward sweep load flow algorithm, which consists of two steps:

Backward sweep: In this step, the load current of each node of a distribution network having *N* number of nodes is determined as:

$$\bar{I}_L(m) = \left\{\frac{P_L(m) - jQ_L(m)}{\bar{V}^*(m)}\right\} \qquad [\, m = 1,2,3 \ldots \ldots \ldots N] \tag{5.8}$$

where, $P_L(m)$ and $Q_L(m)$ represent the active and reactive power demand at node *m* and the overbar notation $(\bar{x})$ indicates the phasor quantities, such as $\bar{I}_L, \bar{V}^*$. Then, the current in each branch of the network is computed as:

$$\bar{I}(mn) = \bar{I}_L(n) + \sum_{m\in\Gamma} \bar{I}_L(m) \tag{5.9}$$

where, the set Γ consists of all nodes which are located beyond the node *n*. To incorporate the DG model, the active and reactive power demand at the node at which a DG unit is placed, say, at node *i*, is modified by:

$$P_{D\_i}^{with\_DG} = P_{D\_i}^{without\_DG} - P_{G\_i}^{DG} \tag{5.10}$$

$$Q_{D\_i}^{with\_DG} = Q_{D\_i}^{without\_DG} \mp Q_{G\_i}^{DG} \tag{5.11}$$

***Forward sweep*:** This step is used after the backward sweep so as to determine the voltage at each node of a distribution network as follows:

$$\bar{V}(n) = \bar{V}(m) - \bar{I}(mn)Z(mn) \tag{5.12}$$

where, nodes *n* and *m* represent the receiving and sending end nodes, respectively for the branch *mn* and $Z(mn)$ is the impedance of the branch.

(B) GA Optimization for DG allocation

In this analysis proposed adaptive GA is used for optimization of DG location and size. Optimization procedure is same as discussed in section 4.4 and section 4.5. Only the load flow is fuzzyfied and the GA is in adaptive in nature. The flowchart for the uncertainty in load and generation approach is presented below.

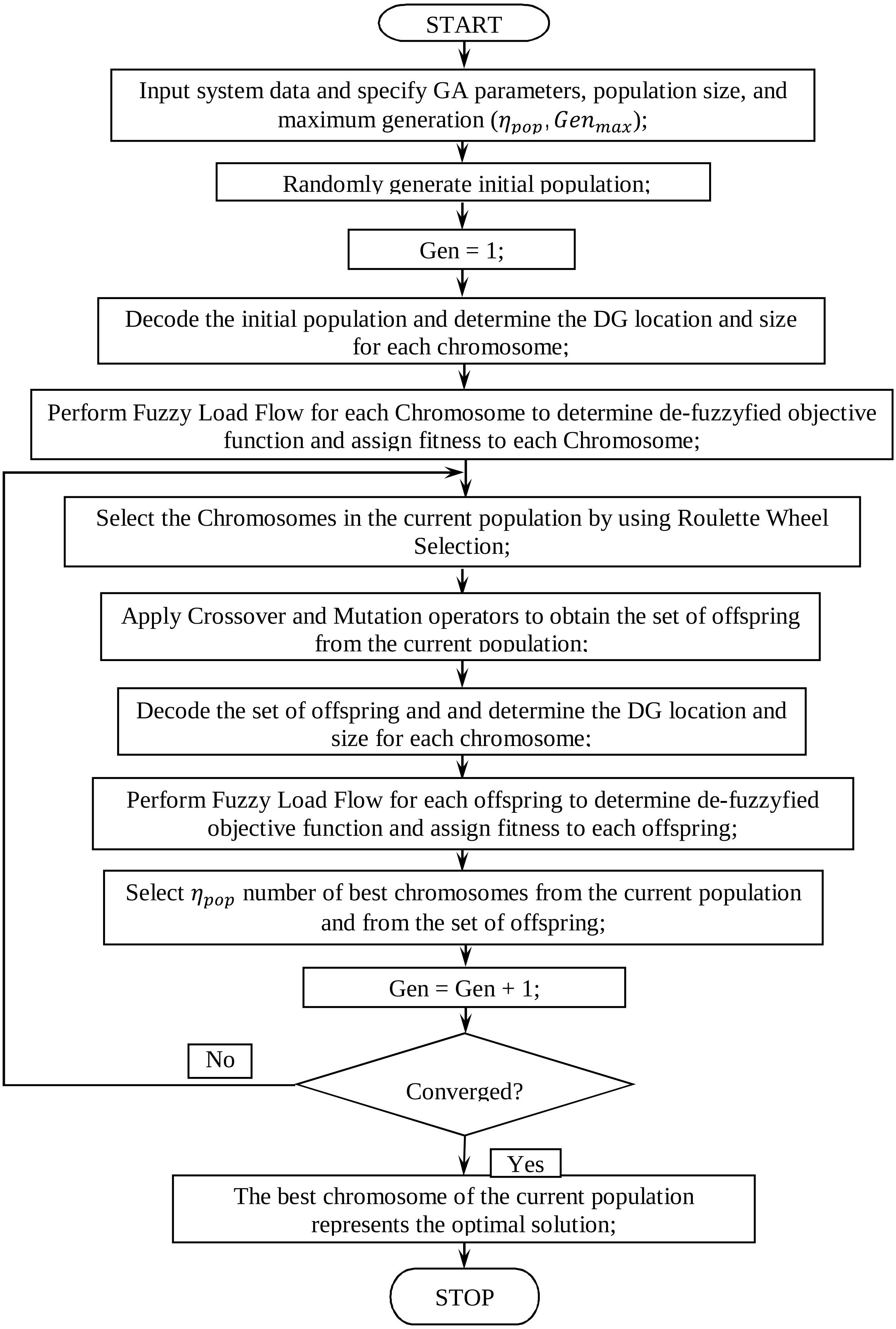


Figure 5.6. Flowchart for uncertainty in Load and Generation with GA optimization.

5.5 CASE STUDY FOR UNCERTAINTY IN LOAD AND GENERATION

5.5.1 Deterministic load and generation analysis

Table 5.1 Study for deterministic load of 0.6 p.u. on test systems with Ga#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power		No. of Tap	No. of CB	Total CB Reactive Power (kW)	Minimum Active Power Loss (kW)	Minimum Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
			Active Power (kW)	Reactive Power (kVAR)							
Base	System # 1	-	-	-	-	-	-	75.5264	34.4477	0.94755	0.28777
	System # 2	-	-	-	-	-	-	241.251	103.794	0.84120	1.24020
Case # 1 (a)	System # 1	5	1398.0	-	-	-	-	17.115	7.994	0.98560	0.18710
	System # 2	4	1394.0	-	-	-	-	22.128	9.520	0.96155	0.85695
Case # 1 (b)	System # 1	4	1118.4	838.8	-	-	-	4.032	3.636	0.99234	0.14046
	System # 2	5	1115.2	836.4	-	-	-	24.488	10.535	0.97053	0.87447
Case # 1 (c)	System # 1	3	1019.2	-764.4	-	-	-	66.918	29.960	0.96530	0.27684
	System # 2	3	1093.6	-820.2	-	-	-	125.231	53.878	0.88240	1.36410
Case # 2 (a)	System # 1	4	1397.0	-	10	-	-	4.814	2.742	0.99419	0.14526
	System # 2	4	1394.0	-	19	-	-	11.874	5.108	0.96789	0.76714
Case # 2 (b)	System # 1	4	1118.4	838.8	10	-	-	0.164	2.028	0.99487	0.12917
	System # 2	5	1145.2	836.2	20	-	-	14.859	6.393	0.97164	0.78049
Case # 2 (c)	System # 1	3	1115.2	-836.4	9	-	-	36.222	16.880	0.97204	0.23973
	System # 2	3	1115.2	-834.4	20	-	-	104.621	45.011	0.89680	1.30790
Case # 3	System # 1	-	-	-	-	4	1396	41.750	18.292	0.96443	0.23564
	System # 2	-	-	-	-	3	1394	218.801	94.135	0.85533	1.16640
Case # 4	System # 1	-	-	-	10	4	1398	37.337	16.783	0.96768	0.23472
	System # 2	-	-	-	20	3	1390	200.815	86.397	0.87695	1.10720
Case # 5	System # 1	-	-	-	10	-	-	49.156	22.526	0.95545	0.23938
	System # 2	-	-	-	20	-	-	218.739	94.108	0.86491	1.15550

System # 1 and System # 2 with a deterministic load of 0.6 p.u base Load; case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

Table 5.2. Study for deterministic load of 1.0 p.u. on test systems with Ga#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power Active Power (kW)	Total DG Power Reactive Power (kVAR)	No. of Tap	No. of CB	Total CB Reactive Power (kW)	Minimum Active Power Loss (kW)	Minimum Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
Base	System # 1	-	-	-	-	-	-	224.995	102.198	0.90919	0.49031
	System # 2	-	-	-	-	-	-	887.181	381.694	0.68442	2.43820
Case # 1 (a)	System # 1	4	2088.0	-	-	-	-	50.557	24.0396	0.96953	0.32060
	System # 2	5	2095.0	-	-	-	-	92.600	39.839	0.92560	1.30910
Case # 1 (b)	System # 1	5	1678.4	1258.8	-	-	-	17.624	13.135	0.98035	0.25856
	System # 2	6	1679.2	1259.4	-	-	-	89.619	38.557	0.93813	1.30910
Case # 1 (c)	System # 1	3	1433.6	-1075.6	-	-	-	190.731	85.864	0.93621	0.46614
	System # 2	4	1650.4	-1237.8	-	-	-	535.504	230.391	0.82221	2.11770
Case # 2 (a)	System # 1	5	2087.0	-	8	-	-	16.598	9.694	0.97902	0.23973
	System # 2	6	2095.0	-	19	-	-	77.164	33.059	0.93456	1.30910
Case # 2 (b)	System # 1	5	1676.0	1257.0	9	-	-	7.698	4.534	0.98803	0.21735
	System # 2	6	1678.4	1258.8	20	-	-	76.789	33.037	0.95106	1.30830
Case # 2 (c)	System # 1	4	1634.4	-1225.8	10	-	-	128.582	56.112	0.95070	0.36631
	System # 2	4	1658.4	-1243.8	20	-	-	483.191	207.885	0.84036	1.9143
Case # 3	System # 1	-	-	-	-	4	2099	128.676	57.0404	0.93814	0.40236
	System # 2	-	-	-	-	4	2096	786.995	338.591	0.71626	2.25760
Case # 4	System # 1	-	-	-	7	4	2091	120.470	56.114	0.94519	0.39981
	System # 2	-	-	-	20	4	2090	716.607	308.308	0.75746	2.12410
Case # 5	System # 1	-	-	-	10	-	-	169.244	77.768	0.91721	0.43167
	System # 2	-	-	-	20	-	-	796.285	342.588	0.73196	2.26360

System # 1 and System # 2 with a deterministic load of 1.0 p.u Load; case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

Table 5.3. Study for deterministic load of 1.6 p.u. and 1.2 p.u. of base load on test systems with Ga#6 optimization

Different Cases	**Different *systems***	**No. of DG**	**Total DG Power**		**No. of Tap**	**No. of CB**	**Total CB Reactive Power (kW)**	**Minimum Active Power Loss (kW)**	**Minimum Reactive Power Loss (kVAR)**	**Min. Node Voltage (Volt)**	**Max Current (Amp)**
			Active Power (kW)	**Reactive Power (kVAR)**							
Base	System # 1	-	-	-	-	-	-	867.295	390.191	0.82031	0.93235
	System # 2	-	-	-	-	-	-	1724.970	742.139	0.53900	3.51230
Case # 1 (a)	System # 1	8	3728.0	-	-	-	-	157.370	68.993	0.96992	0.50919
	System # 2	7	2788.0	-	-	-	-	105.976	45.594	0.93377	1.58111
Case # 1 (b)	System # 1	8	2981.6	2236.2	-	-	-	15.078	10.350	0.98913	0.31447
	System # 2	9	2230.4	1672.8	-	-	-	98.570	42.408	0.94893	1.49520
Case # 1 (c)	System # 1	5	2373.6	-1780.2	-	-	-	568.087	251.991	0.89789	0.77161
	System # 2	6	2157.6	-1618.2	-	-	-	904.432	389.116	0.78680	2.71010
Case # 2 (a)	System # 1	8	3728.0	-	10	-	-	75.704	33.194	0.97236	0.40575
	System # 2	7	2788.0	-	20	-	-	68.896	29.641	0.93155	1.58110
Case # 2 (b)	System # 1	9	2982.4	2236.8	10	-	-	14.111	9.560	0.98427	0.31691
	System # 2	8	2230.4	1672.8	20	-	-	84.1938	36.222	0.94464	1.58060
Case # 2 (c)	System # 1	8	2982.4	-2236.8	10	-	-	494.946	221.613	0.90879	0.74154
	System # 2	8	2229.6	-1672-2	20	-	-	773.428	332.754	0.80058	2.46760
Case # 3	System # 1	-	-	-	-	6	3458.0	374.286	163.569	0.89791	0.66296
	System # 2	-	-	-	-	6	2788.0	1383.72	595.321	0.61354	3.05070
Case # 4	System # 1	-	-	-	9	8	2346.0	374.635	163.135	0.90894	0.65430
	System # 2	-	-	-	20	7	2785.0	1204.72	518.309	0.67753	2.79410
Case # 5	System # 1	-	-	-	10	-	-	508.278	230.667	0.85667	0.72103
	System # 2	-	-	-	20	-	-	1052.34	452.751	0.68671	2.63640

System # 1 and System # 2 with a deterministic load of 1.6 p.u. and 1.2 p.u. load respectively; case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

5.5.2 Possibilistic load and generation analysis

Table 5.4. Study for possibilistic load of 0.4 p.u to 1.4 p.u. on test systems with Ga#6 optimization

Different Cases	Different systems	No. of DG	Total DG Power		No. of Tap	No. of CB	Total CB Reactive Power (kW)	Minimum Active Power Loss (kW)	Minimum Reactive Power Loss (kVAR)	Min. Node Voltage (Volt)	Max Current (Amp)
			Active Power (kW)	Reactive Power (kVAR)							
Base	System # 1	-	-	-	-	-	-	201.193	91.435	0.91416	0.46444
	System # 2	-	-	-	-	-	-	764.177	328.774	0.70890	2.25270
Case # 1 (a)	System # 1	7	2213.0	-	-	-	-	49.174	21.871	0.98114	0.29830
	System # 2	7	2207.0	-	-	-	-	59.896	25.769	0.94218	1.24160
Case # 1 (b)	System # 1	6	1770.4	1327.8	-	-	-	10.003	9.095	0.98860	0.22293
	System # 2	9	1765.6	1324.2	-	-	-	58.806	25.300	0.95715	1.18690
Case # 1 (c)	System # 1	4	1529.6	-1147.2	-	-	-	176.867	78.843	0.94305	0.44430
	System # 2	6	1759.2	-1319.4	-	-	-	480.434	206.698	0.83001	1.88320
Case # 2 (a)	System # 1	6	2213.0	-	10	-	-	12.781	6.527	0.98875	0.19997
	System # 2	6	2206.0	-	18	-	-	39.247	16.885	0.94462	1.24160
Case # 2 (b)	System # 1	5	1766.4	1324.8	10	-	-	4.004	2.892	0.99454	0.18590
	System # 2	8	1765.6	1324.2	19	-	-	47.984	20.644	0.95665	1.24280
Case # 2 (c)	System # 1	5	1700.0	-1275.0	10	-	-	133.115	59.834	0.95312	0.40433
	System # 2	5	1763.2	-1322.4	20	-	-	436.000	187.581	0.86231	1.87720
Case # 3	System # 1	-	-	-	-	5	2213.0	116.100	50.726	0.94395	0.37919
	System # 2	-	-	-	-	4	2207.0	675.519	290.630	0.73967	2.08190
Case # 4	System # 1	-	-	-	8	5	2212.0	108.008	47.871	0.94566	0.37645
	System # 2	-	-	-	20	5	2203.0	621.814	267.525	0.77587	1.97270
Case # 5	System # 1	-	-	-	10	-	-	148.999	68.500	0.92255	0.40624
	System # 2	-	-	-	20	-	-	691.949	297.699	0.75144	2.10830

System # 1 and System # 2 with a possibilistic load of 0.4 p.u to 1.4 p.u. base Load; case#1(a), unity p.f. DG; case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging; case#2(a), unity p.f. DG with OLCT; case#2(b), DG operating at 0.8 p.f. leading with OLTC.; case#2(c), DG operating at 0.8 p.f. lagging with OLTC; case#3, capacitor bank; case#4, capacitor bank with OLTC; case#5, only OLTC.

5.5.3 Multiple run for deterministic and possibilistic load and generation

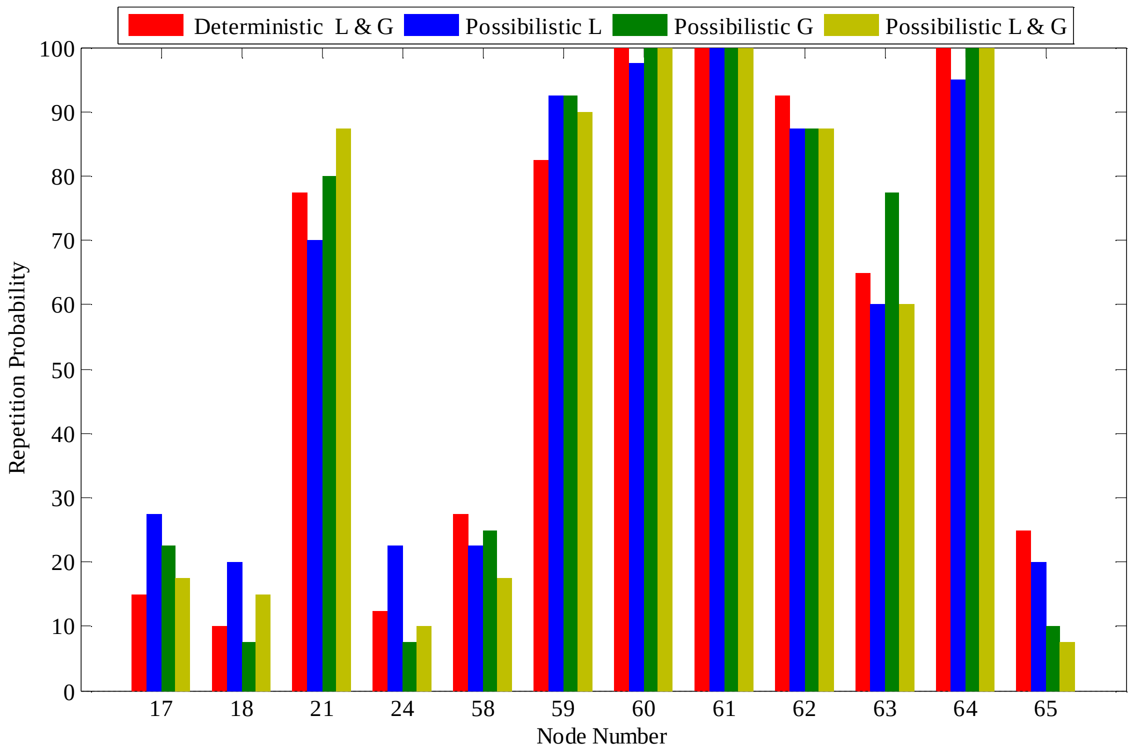


Figure 5.7. System #1, DG location repetition probability for multiple run for the case#1(b); case#1(b), DG operating at 0.8 p.f. leading;

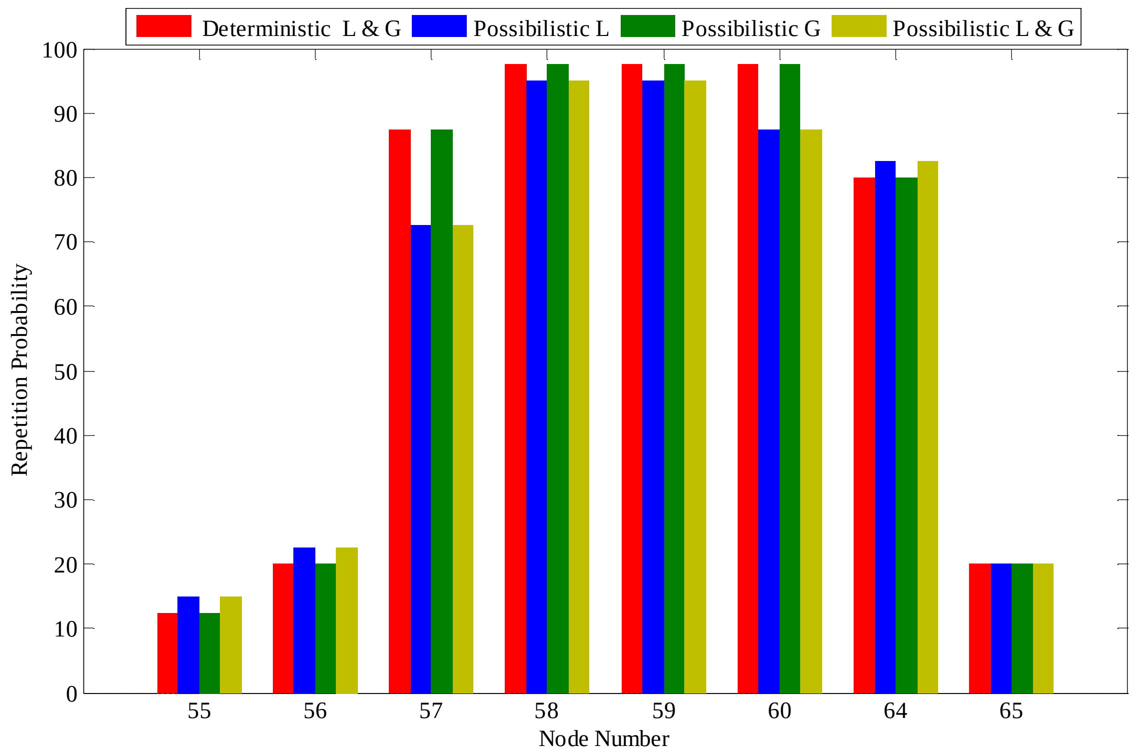


Figure 5.8. System #1, DG location repetition probability for multiple run for the case#1(c); case#1(c), DG operating at 0.8 p.f. lagging;

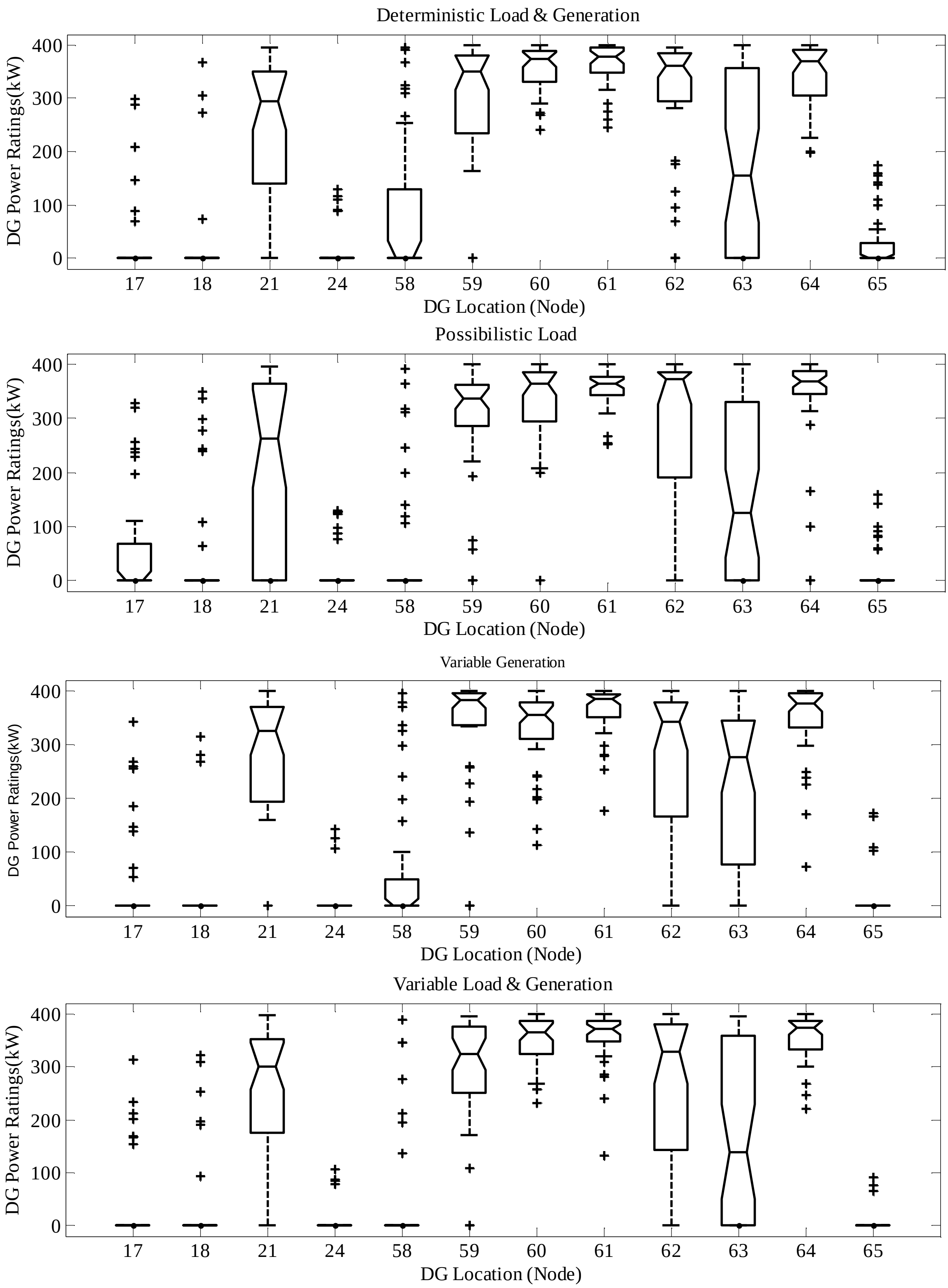


Figure 5.9. System #1, DG power rating variation for candidate nodes in multiple run for the case#1(b); case#1(b), DG operating at 0.8 p.f. leading;

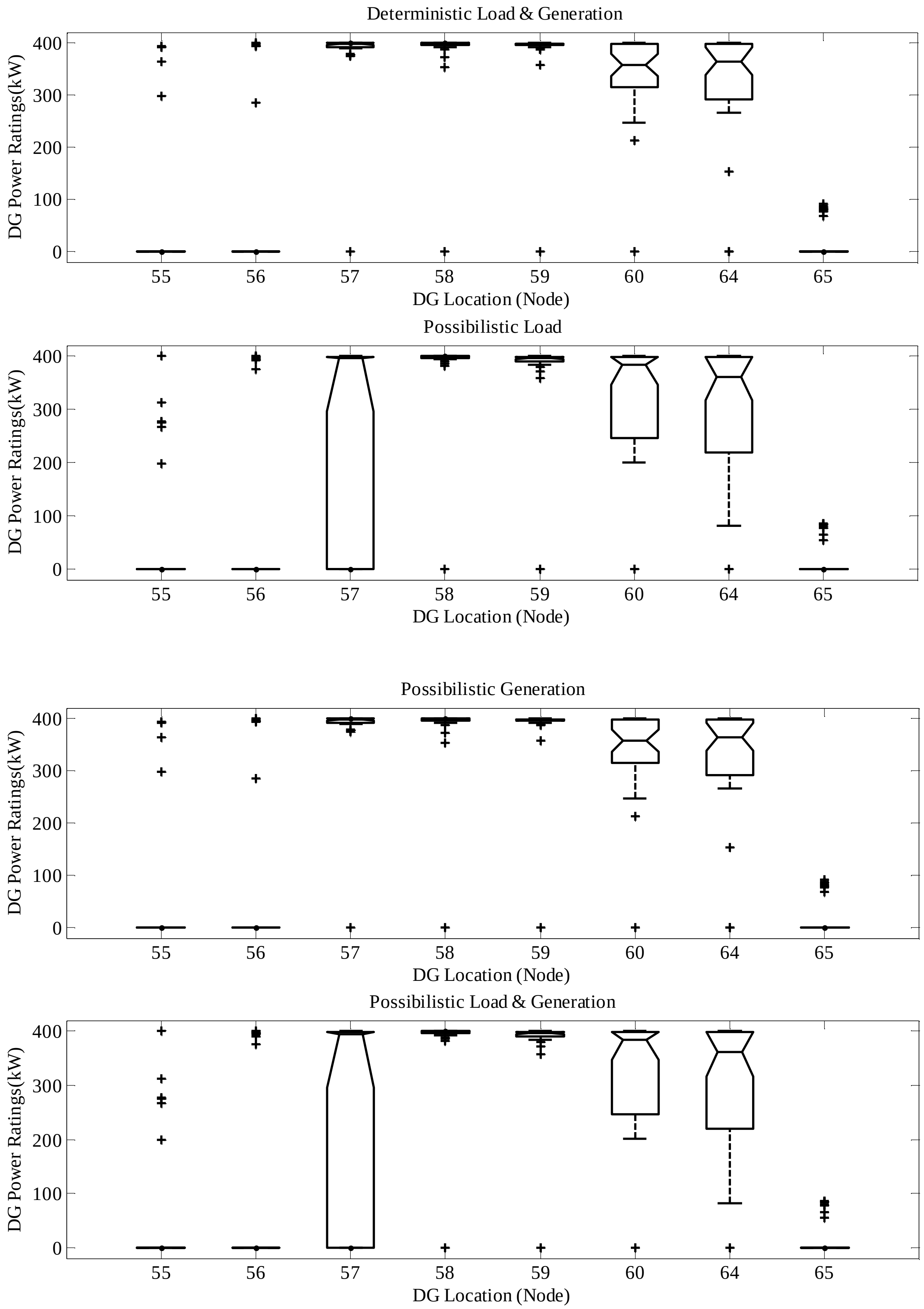


Figure 5.10. System #1, DG power rating variation for candidate nodes in multiple run for the case#1(c); case#1(c), DG operating at 0.8 p.f. lagging;

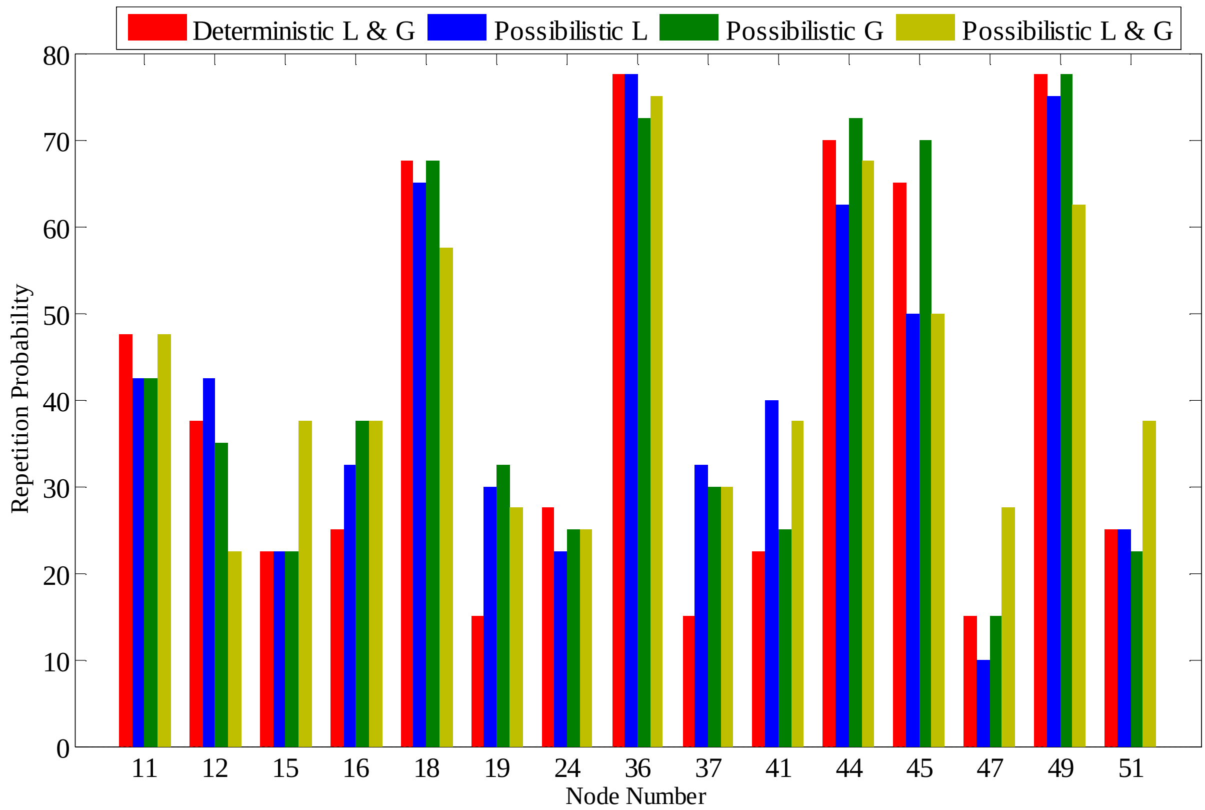


Figure 5.11. System #2, DG location repetition probability for multiple run for the case#1(b); case#1(b), DG operating at 0.8 p.f. leading

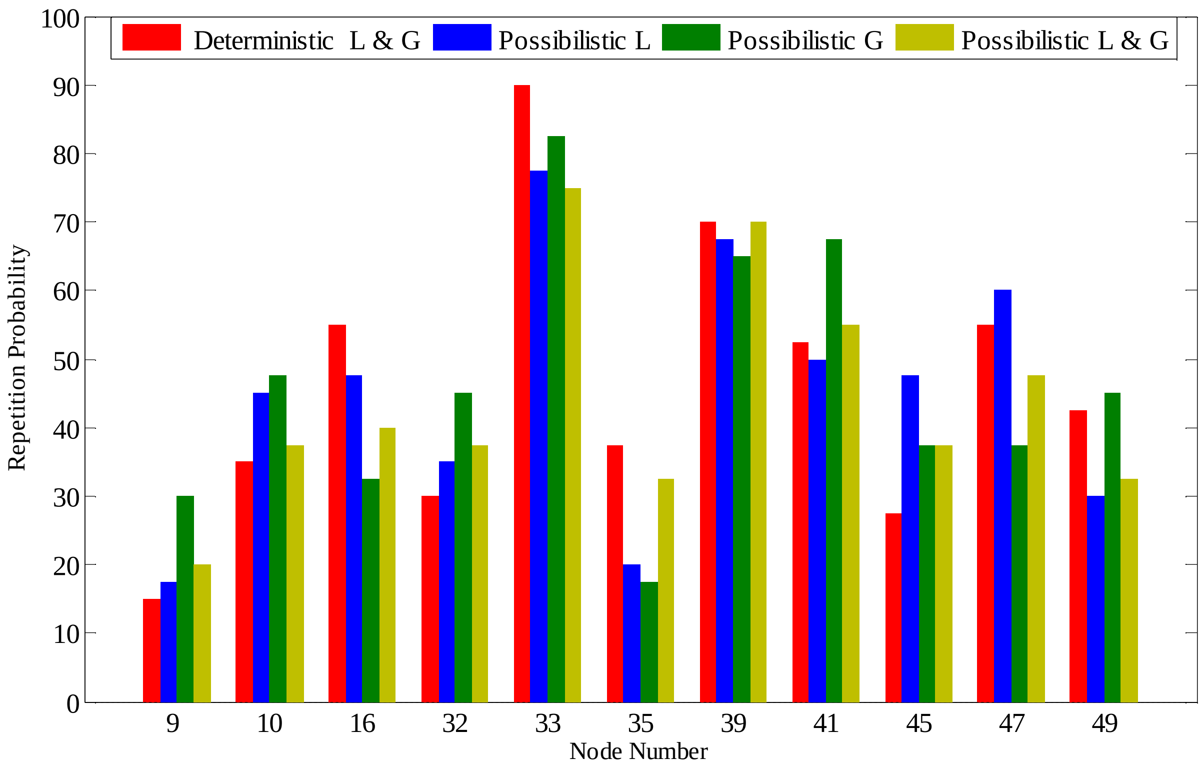


Figure 5.12. System #2, DG power rating variation for candidate nodes in multiple run for the case#1(c); case#1(c), DG operating at 0.8 p.f. lagging

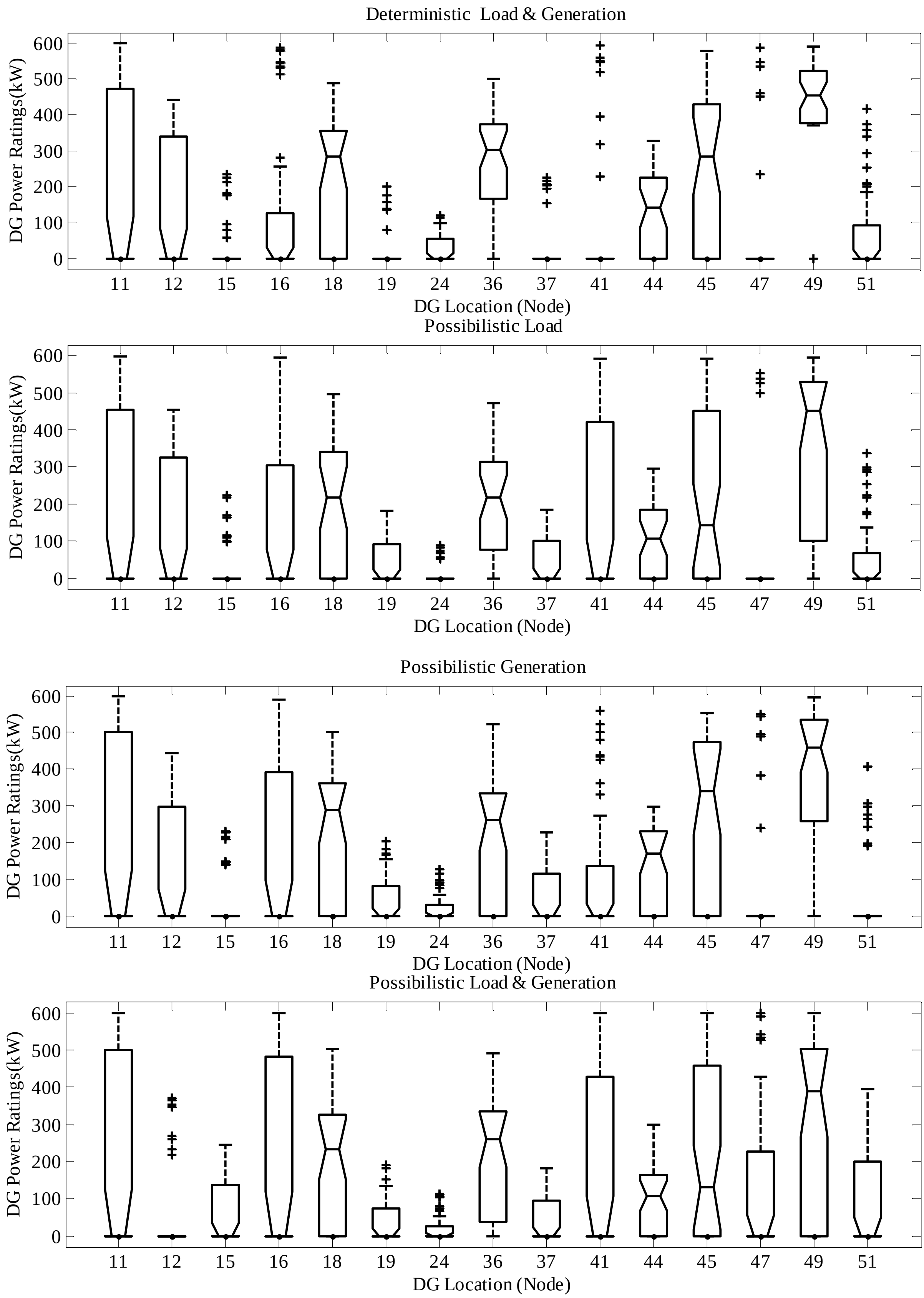


Figure 5.13. System #2, DG power rating variation for candidate nodes in multiple run for the case#1(b); case#1(b), DG operating at 0.8 p.f. leading;

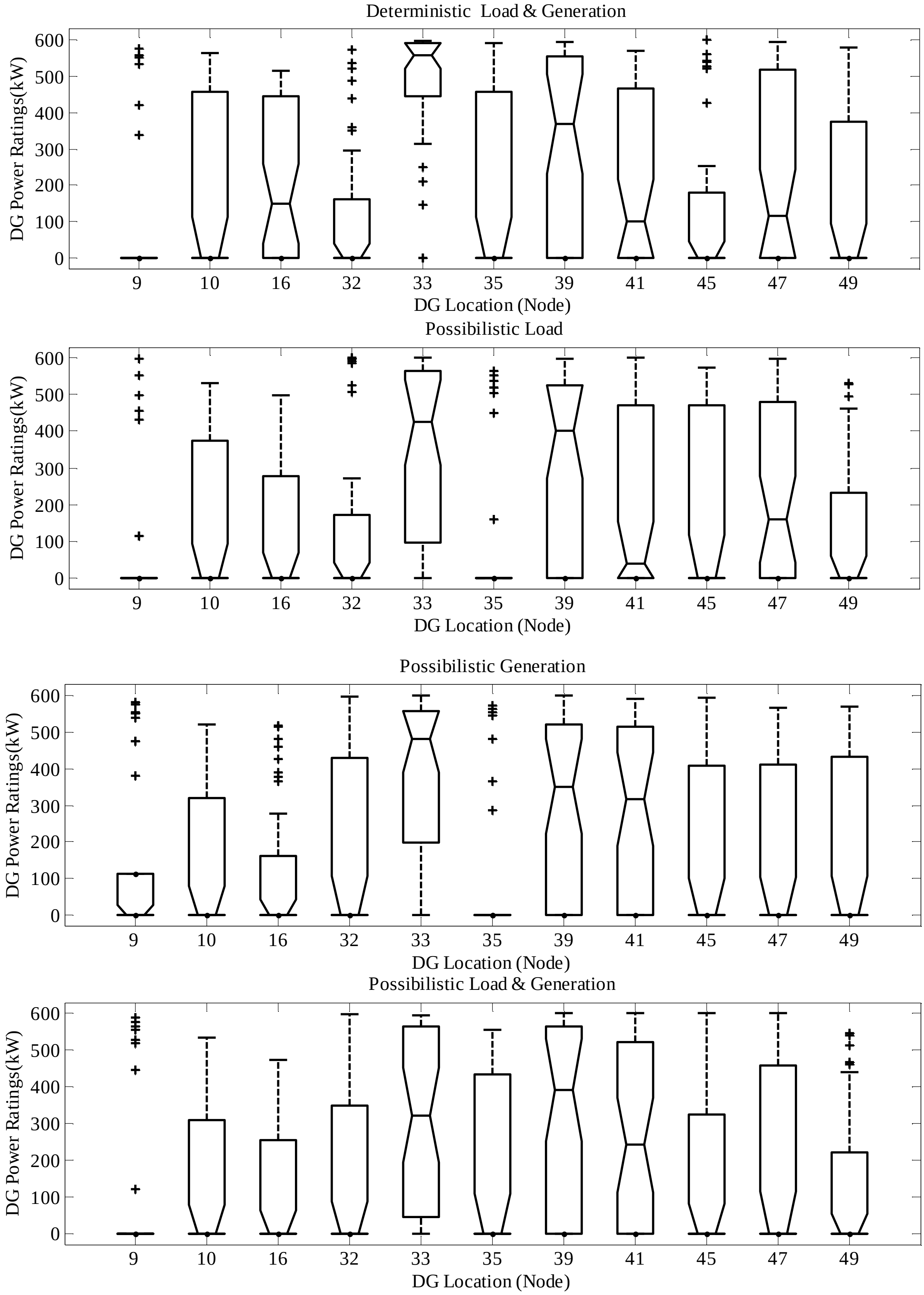


Figure 5.14. System #2, DG power rating variation for candidate nodes in multiple run for the case#1(c);.; case#1(c), DG operating at 0.8 p.f. lagging;

Table 5.5. Effective nodes DG ratings median value for various cases

System #1 (69 node)					System #2 (52 node)				
Case#1(b)					Case#1(b)				
Node no.	#AA	#BB	#CC	#DD	Node no.	#AA	#BB	#CC	#DD
21	293.5	262.5	325.5	300.5	18	282.5	217	288	233
59	351	337	382	324	36	303	218	260	258.5
60	373.5	365	356	366	44	140	107.5	170.5	108
61	377.5	363	385	371	45	284.5	141	336	129.5
62	362	373	343	328	49	454	452	460	389
63	155.5	124	277.5	139.5					
64	368.5	369	376	374					
Case#1(c)					Case#1(c)				
57	397.5	395	397.5	395	16	149.5	0	0	0
58	398	398	398	398	33	557.5	425.5	480.5	322.5
59	397	397	397	397	39	369.5	401	351.5	392
60	357.5	384.5	357.5	384.5	41	100	37	317.5	241
64	364	361	364	361	47	115.5	159.5	0	0

Case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging and #AA; Deterministic Load and Generation; #BB; Possibilistic Load; #CC; Possibilistic Generation; #DD; Possibilistic Load and Generation

5.5.4 Multiple run uncertainty analysis with different system and GA parameter

With a new system and GA parameter the optimization is carried out for three different cases (i.e. case#1(a), case#1(b), and case #1(c)). This system and GA parameter are also taken for the analysis of uncertainty with different DG rating.

Table 5.6. GA and network parameters considered for the optimization process

GA parameter		**Network parameter**	
Population size (η_{max})	80	DGs power rating range (P_{DG}):	(50 – 600) kW
Maximum Generation (Gen_{max})	270	Minimum Voltage (V_{min}):	System#2: 0.90 p.u.
Crossover probability (Ω_c)	adaptive	Maximum Thermal Limit (I_{max}):	System#2: 1.2 p.u.
Mutation Probability (Ω_m)	0.005	Maximum number of DG (ψ_n):	5
Maximum iteration for load flow	300	DG penetration limit	Max 50% of total load
Accuracy label in load flow	10^{-9}		

Table 5.7. Effective nodes DG ratings median value for various cases

System #2 (DG range 50-600)				
Case#1(a)				
Node no.	**#AA**	**#BB**	**#CC**	**#DD**
11	0	0	147.5	0
16	0	483.5	249	0
18	329.5	0	117.5	198
36	0	0	0	0
45	519	502.5	445.5	528.5
47	501.5	466.5	508.5	453.5
49	540.5	543	554.5	518.5
Power Loss	133.03	110.56	103.15	182.39
Minimum Voltage	0.85937	0.88407	0.89363	0.83514
Case#1(b)				
11	217	439.5	225	446
16	463	0	466.5	0
18	0	278.5	0	114.5
36	311.5	0	184.5	208
41	0	510	471.5	529
49	527	552	557.5	552
Power Loss	194.04	132.47	113.38	122.78
Minimum Voltage	0.86286	0.90697	0.92554	0.90436
Case#1(c)				
33	506.5	347.5	263.5	550.5
39	139	512.5	50.5	488.5
41	439.5	78.5	546	114.5
47	0	298.5	0	0
Power Loss	592.16	563.34	626.14	584.27
Minimum Voltage	0.78064	0.78370	0.76967	0.77897

Case#1(b), DG operating at 0.8 p.f. leading; case#1(c), DG operating at 0.8 p.f. lagging and #AA; Deterministic Load and Generation; #BB; Possibilistic Load; #CC; Possibilistic Generation; #DD; Possibilistic Load and Generation

5.5.5 Multiple run uncertainty analysis with different DG rating limit

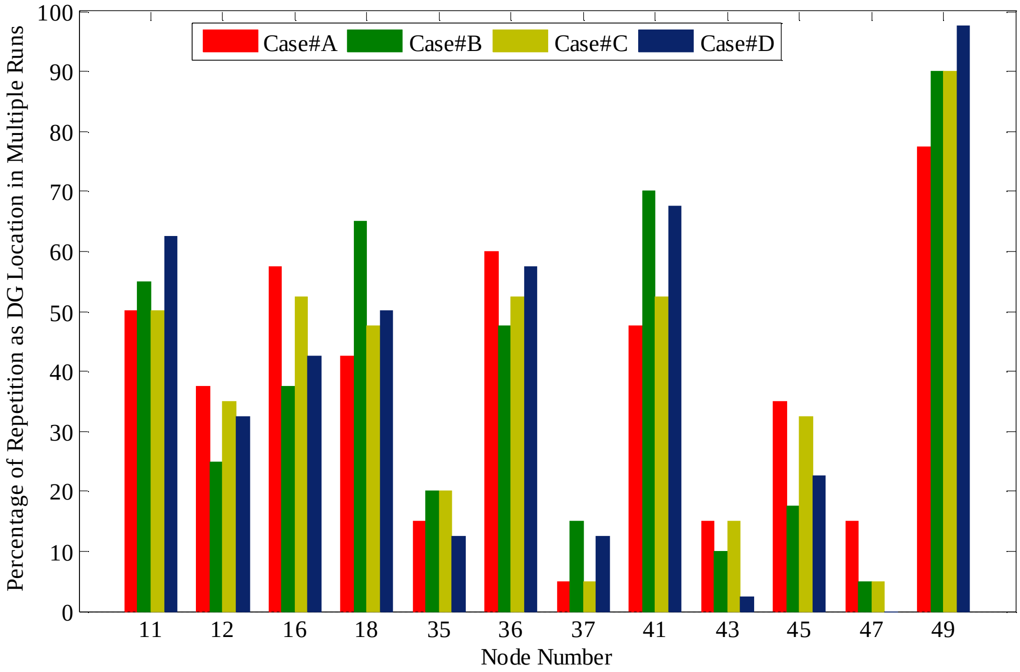


Figure 5.15. Percentage of repetition as DG location in multiple runs for System #2 with a DG rating limit of (50-600) kW

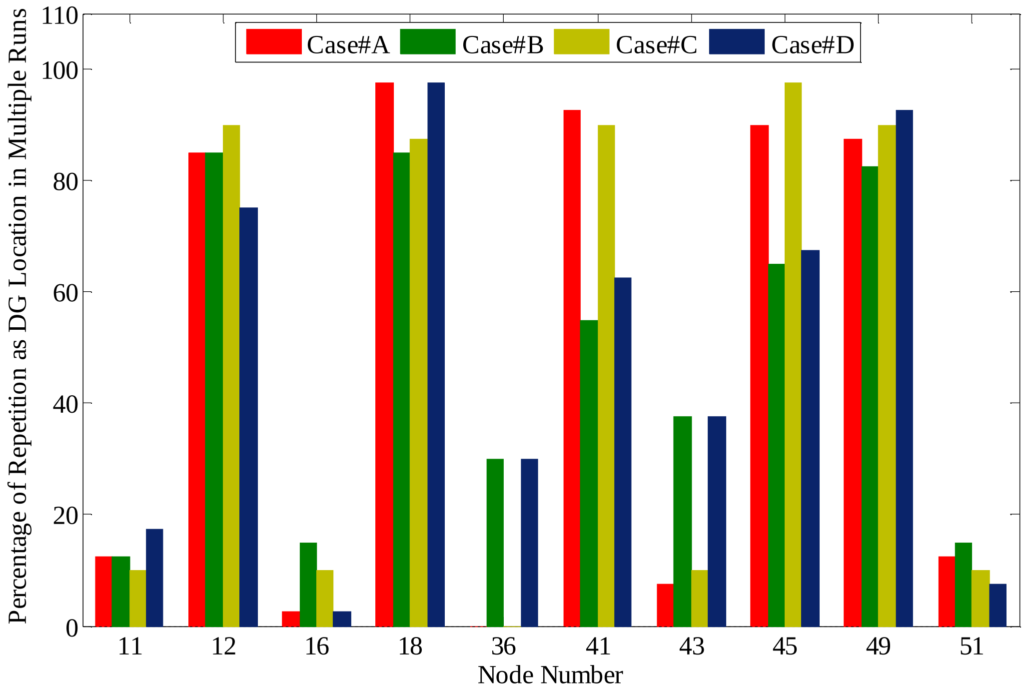


Figure 5.16. Percentage of repetition as DG location in multiple runs for System #2 with a DG rating limit of (50-600) kW

Case#1(b), DG operating at 0.8 p.f. leading; and Case# A, Deterministic Load and Generation; Case# B, Possibilistic Load; Case# C, Possibilistic Generation; Case# D, Possibilistic Load and Generation

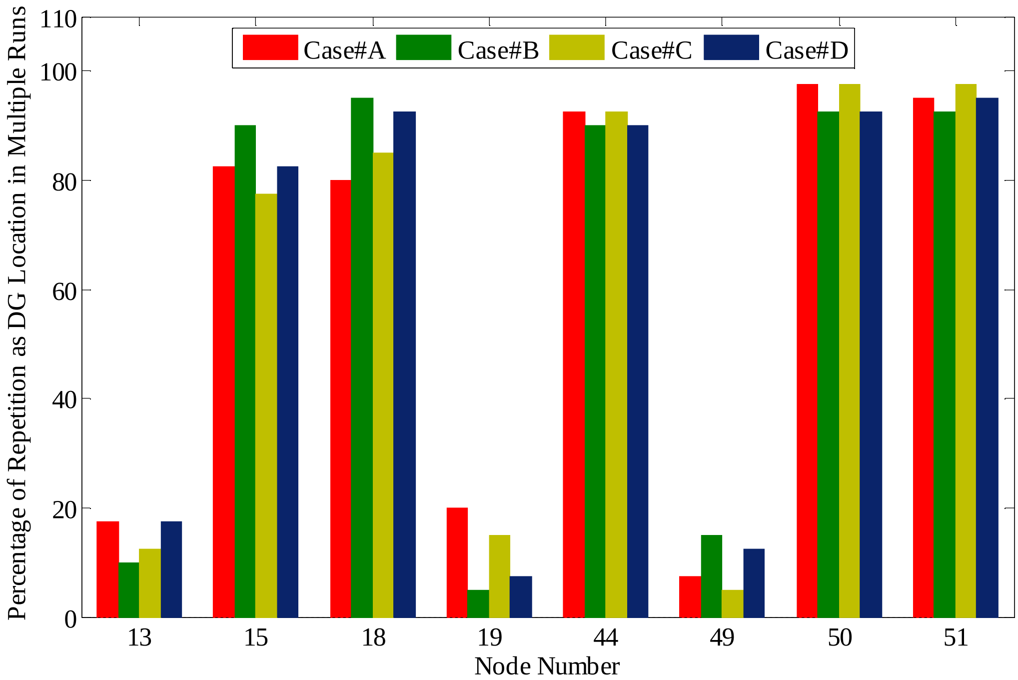


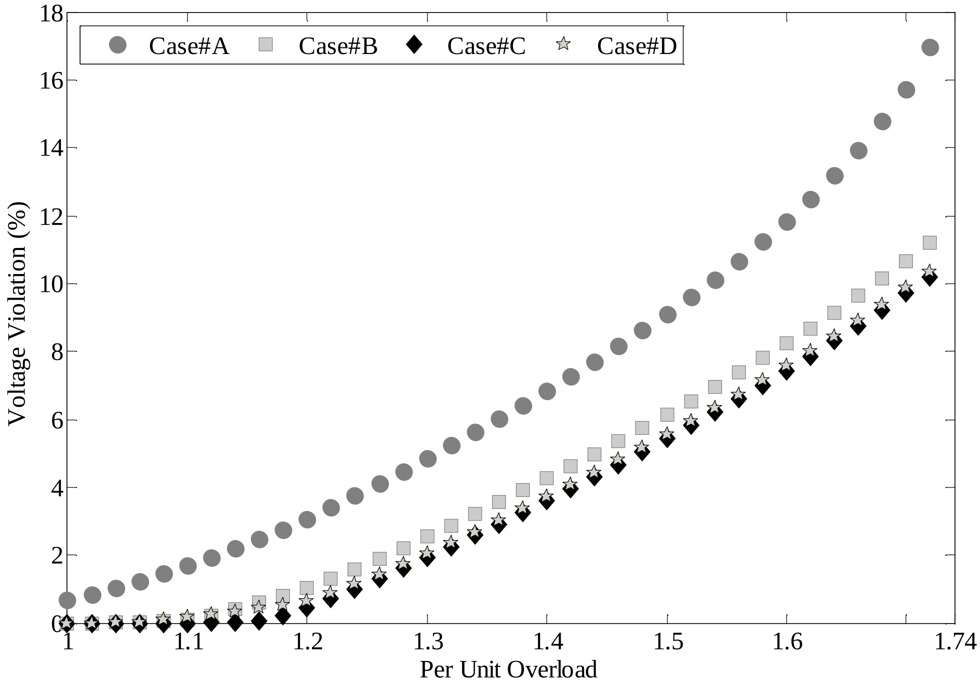
Figure 5.17. Percentage of repetition as DG location in multiple runs for System #2 with a DG rating limit of (50-200) kW

Case#1(b), DG operating at 0.8 p.f. leading; and Case# A, Deterministic Load and Generation; Case# B, Possibilistic Load; Case# C, Possibilistic Generation; Case# D, Possibilistic Load and Generation

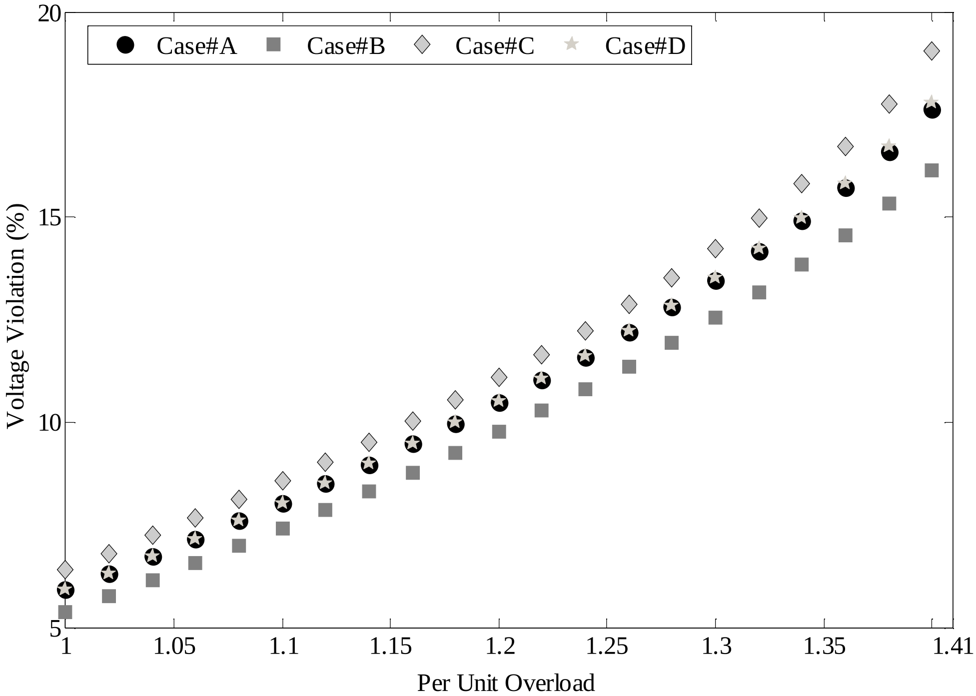
In uncertainty analysis with different DG rating limit it is concluded that the location of DG is changes with the DG ratings.

5.5.6 Violation of system constraint in overloading condition

System#2 is step wise overloaded with DGs, DGs are incorporated into the system with the data got from the uncertainty analysis shown in Table 5.7.

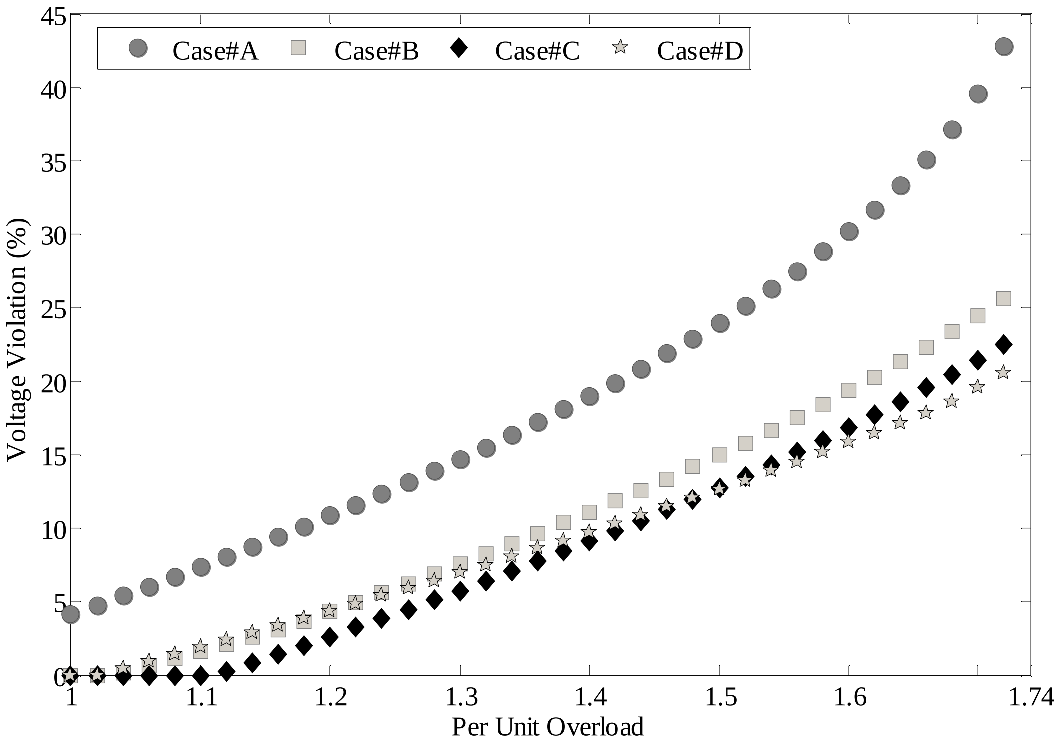


(A)

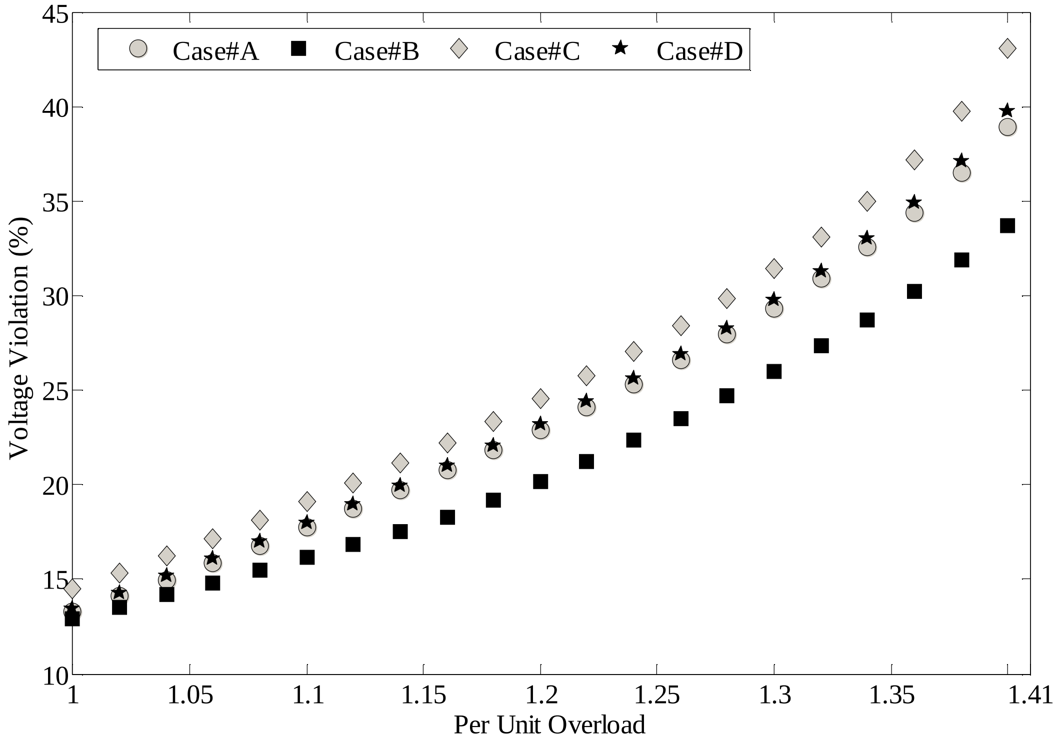


(B)

Figure 5.18. Average voltage violation with per unit overload of system #2 with a DG rating limit of (50-600)kW; (A) average voltage violation with per unit overload for case#1(b), (B) average voltage violation with per unit overload for case#1(c)



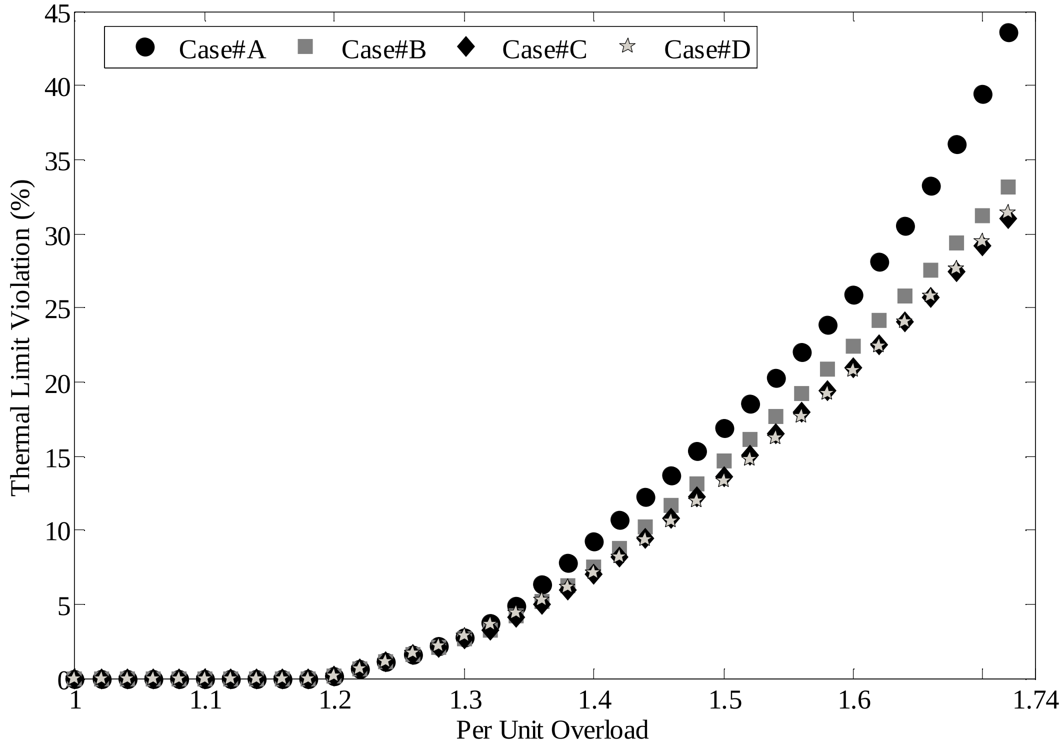
(A)



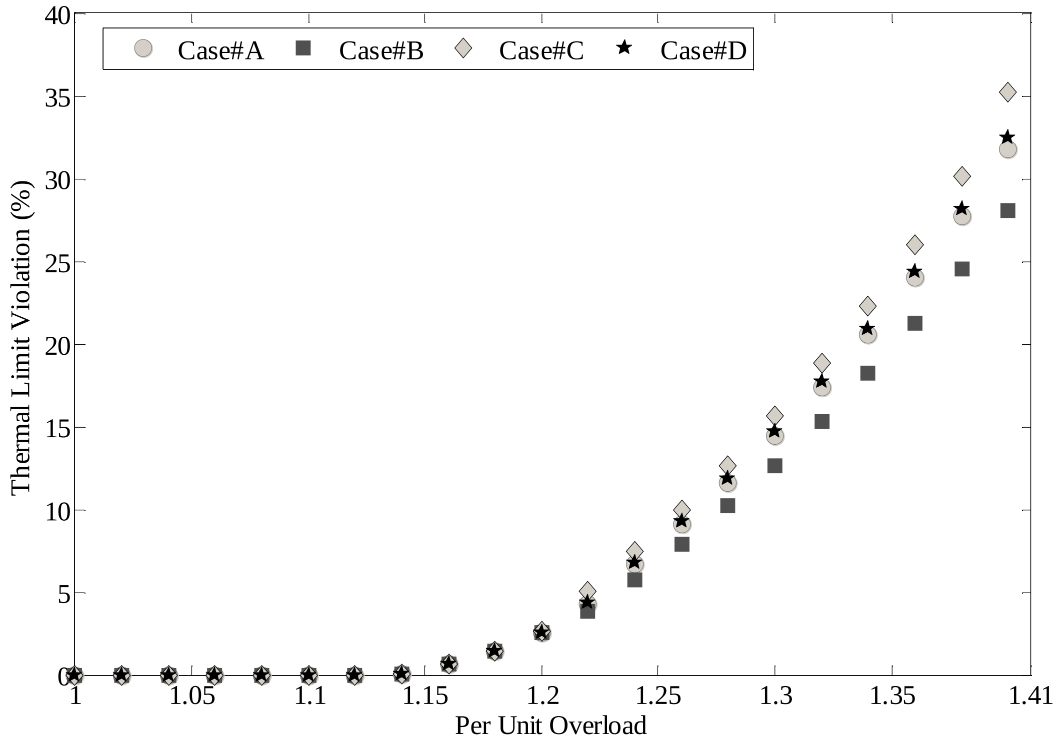
(B)

Figure 5.19. Maximum voltage violation with per unit overload of system #2 with a DG rating limit of (50-600) kW

(A) Maximum voltage violation with per unit overload for case#1(b), (B) maximum voltage violation with per unit overload for case#1(c)



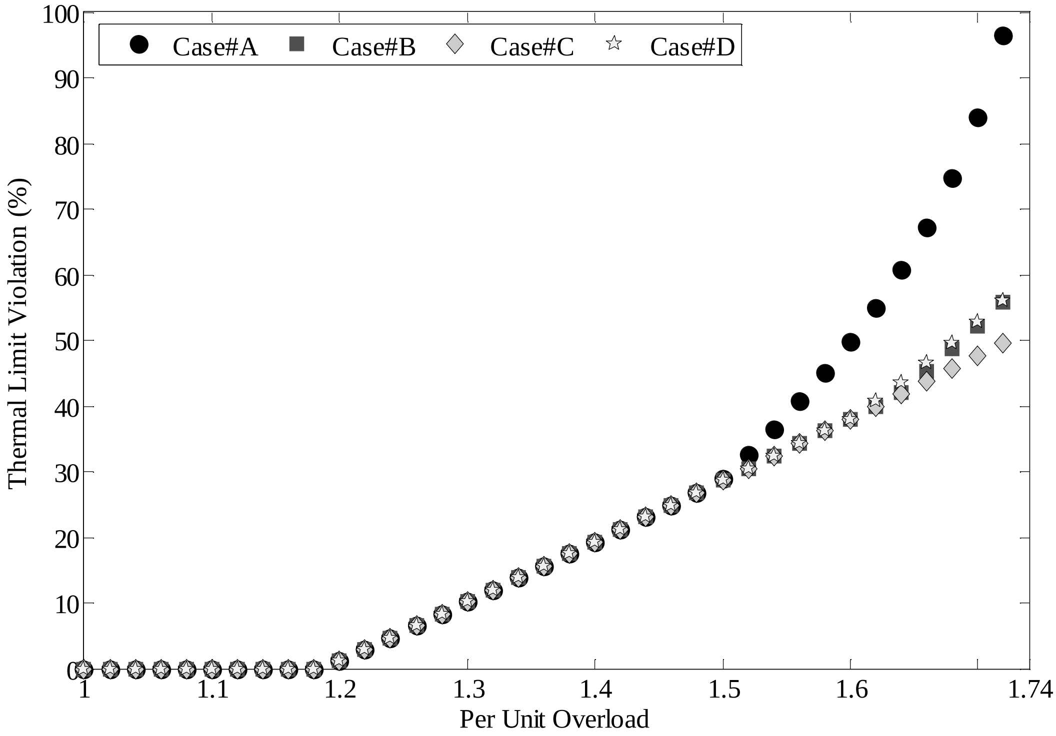
(A)



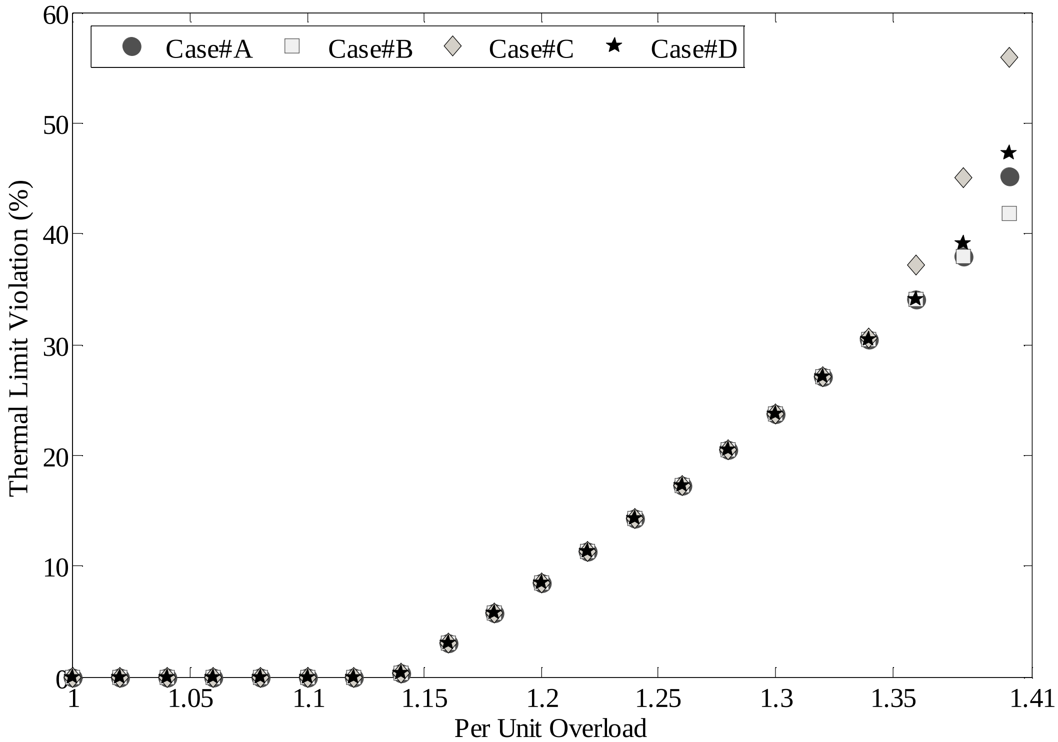
(B)

Figure 5.20. Average current violation with per unit overload of system #2 with a DG rating limit of (50-600)

(A) Average current violation with per unit overload for case#1(b), (B) average current violation with per unit overload for case#1(c)



(A)



(B)

Figure 5.19. Maximum current violation with per unit overload of system #2 with a DG rating limit of (50-600)

(A) Maximum current violation with per unit overload for case#1(b), (B) maximum current violation with per unit overload for case#1(c)

5.6 SUMMARY

In this chapter, a multi-objective optimization method to find the optimal DG sizing and placement in a distribution network was proposed, where the total real power loss of the network were employed as the objective to be minimised. Thus, the load demand at each node and the DG power generation at candidate nodes are considered as a possibilistic variable represented by two different triangular fuzzy number. An IEEE 69-node radial test distribution system and 52-node practical radial systems are used to demonstrate the effectiveness of the proposed methods. The simulation results shows that reduction of power loss in distribution system is possible and all node voltages variation can be achieved within the required limit if DG are optimally placed in the system. Induction DG placement into the distribution system also give a better performance from capacitor bank placement. In modern load growth scenario uncertainty load and generation model shows that reduction of power loss in distribution system is possible and all node voltages variation can be achieved within the required limit without violating the thermal limit of the system.

CHAPTER-6

CONCLUSION AND SCOPE FOR FUTURE WORK

6.1 CONCLUSIONS

The installation of DG units in power distribution networks is becoming more prominent. Consequently, utility companies have started to change their electric infrastructure to adapt to DGs due to the benefits of DG installation on their distribution systems. These benefits include reducing power losses, improving voltage profiles, reducing emission impacts and improving power quality. Additional benefits are avoiding upgrading the present power systems and preventing a reduction of T&D network capacity during the planning phase. Nevertheless, achieving these benefits depends highly on the capacity of the DG units and their installation placement in the distribution systems.

In this work, an innovative approach for management of DG power is represented. The proposed method deals with optimal selection of nodes for the placement and size of the DG by using GA. The load flow problem has been solved by forward/backward load flow methodology. The rating and location has been optimised using Genetic Algorithm. In GA, coding is developed to carry out the allocation problem, which is identification of location and rating by one dimensional array. The effectiveness of the approach is demonstrated on the IEEE 69-node reliability test system and a practical 52-node system.

If DGs are connected to the system, the simulation results concludes that reduction of active power loss in distribution system is possible and all node voltages variation can be achieved within the required limit. Multi-objective optimization give the better optimal result then the single-objective optimization. Induction DGs are connected into the systems power loss and voltage profile is better from when the capacitor bank is connected into the systems, though the induction DGs are consuming reactive power from the system where extra amount of power loss is occur due to reactive power flow through the line.

In some of the IGA have only adaptive crossover probability or mutation probability where other one is fixed. But in some cases both are adaptive. Basically in the most of the IGA, crossover and mutation probability is directly related to the fitness function of the population. It can be divided into two category. In the first category it depends upon the maximum and minimum fitness of the population. Due to this either crossover or mutation or both are in partial adaptive in nature for all population of a single generation (i.e. fixed for all matting chromosomes). Or we can say generation wise adaptive in nature. But when either crossover or mutation or both depends upon individual matting chromosome pair fitness and maximum and minimum fitness of the population it become adaptive in nature for all population of a single generation (i.e. different for all matting chromosomes). Thus in this second category, crossover and mutation is not only generation wise also population wise adaptive in nature. By considering all the concept the proposed adaptive GA is based on second category where only crossover probability is adaptive in nature and which is used for optimal DG allocation and size problem. The adaptive crossover probability is directly depends upon the present generation maximum and minimum fitness and the matting chromosome fitness.

The proposed adaptive GA gives the most satisfactory and acceptable result among all the GA approach is considered in the study. The proposed GA give the better result in all part of optimization (i.e. in case for minimum voltage and power loss). The convergence criteria of the proposed adaptive GA is well acceptable. The crossover probability of proposed GA is fully adaptive in nature (i.e. it is not only generation wise also population wise adaptive in nature). The quick convergence of GA and stuck in a local minima can be avoided by this adaptive crossover approach. Synchronous DG are profitable application in all type of system also induction DG are considerable profitable though they consumed reactive power from the system. Installation of induction DG in a very week distribution system is better than the capacitor placement.

In modern load growth scenario probabilistic load and generation model shows that the system, reduction of power loss in distribution system is possible and all node voltages variation can be achieved within the required limit without violating the thermal limit of the system. From the analysis of load and generation uncertainty, system#1 gives a better performance for both synchronous and induction DG. Though the system#2 give a better performance with synchronous DG but with induction DG it give very poor performance. In normal operating condition system#2 have huge power loss with a very poor voltage profile. Due to this when then the induction DG are connected to the system it consumed a large amount of reactive power from the system and it over loaded the system where the system is already hugely over loaded. The management approach presented in work is suitable to be integrated into energy management scheme under smart grid concept. From the study the following conclusions are drawn.

1. The compensation is yielding leading to increase in voltage profile, reduction in losses.
2. The developed algorithm is effective in interpreting the allocation of distributed generator for different number of candidate nodes and distributed generator sizes.
3. The developed algorithm is also effective in interpreting the allocation of tap changing transformer for different number of candidate branch's and tap settings.
4. Even without DG reactive power the voltage could be maintain within ±5 % of the rated voltage. This is due to the fact that even DG injecting power, voltage drop in the line is smaller due to smaller current flowing from upstream and the action of main substation transformer OLCT.
5. Induction DGs placement is better from the capacitor bank placement distribution system.
6. Adaptive GA have better performance over basic GA on the issue of DG allocation.
7. In very weak system placement of induction DG are not favourable.

6.2 SCOPE FOR FUTURE WORK

The completion of research project opens the avenues for work in many other related areas. The following areas are identified for future work:

1. The same work can be extended to 119 node networks or more.
2. Optimization process has been carried out on basic genetic algorithm optimization process. The improved version of genetic algorithm is available and can be applied in this networks for better optimization.
3. The study has been carried out on balanced distribution networks. The DGs allocation problem can be extended to unbalanced distribution networks.
4. The boundary conditions (tap change settings, DGs rating, total DGs power injection) can be modified and applied into the networks.
5. The DGs allocation problem can be extended for DGs reactive power optimization. DG technology that fit this requirement for example are **micro-turbines generation networks** and **fuel cell**. These two technologies can be used to generate both electricity and thermal power.

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APPENDIX A

69-Node Radial Distribution Networks Data

This Appendix contains the data for the 69-node RDS used for this thesis project. This networks was also used in [34].

Table A.l gives the Node data for the 69-node RDS. Table A.2 gives the Line data for the different loops within the 69-node RDS.

Table A.1: The 69-node radial distribution networks Line data.

Node No.	Node code	Voltage Mag.	Angle Degree	Load		Generator		Injected			
				kW	kVAR	MW	MVAR	Qmin	Qmax	MVAR	
1	1	1	0	0	0	0	0	0	0	0	1
2	0	1	0	0	0	0	0	0	0	0	1
3	0	1	0	0	0	0	0	0	0	0	1
4	0	1	0	0	0	0	0	0	0	0	1
5	0	1	0	0	0	0	0	0	0	0	1
6	0	1	0	2.6	2.2	0	0	0	0	0	1
7	0	1	0	40.4	30	0	0	0	0	0	1
8	0	1	0	75	54	0	0	0	0	0	1
9	0	1	0	30	22	0	0	0	0	0	1
10	0	1	0	28	19	0	0	0	0	0	1
11	0	1	0	145	104	0	0	0	0	0	1
12	0	1	0	145	104	0	0	0	0	0	1
13	0	1	0	8	5.5	0	0	0	0	0	1
14	0	1	0	8	5.5	0	0	0	0	0	1
15	0	1	0	0	0	0	0	0	0	0	1
16	0	1	0	45.5	30	0	0	0	0	0	1
17	0	1	0	60	35	0	0	0	0	0	1
18	0	1	0	60	35	0	0	0	0	0	1
19	0	1	0	0	0	0	0	0	0	0	1
20	0	1	0	1	0.6	0	0	0	0	0	1
21	0	1	0	114	81	0	0	0	0	0	1
22	0	1	0	5.3	3.5	0	0	0	0	0	1
23	0	1	0	0	0	0	0	0	0	0	1
24	0	1	0	28	20	0	0	0	0	0	1
25	0	1	0	0	0	0	0	0	0	0	1
26	0	1	0	14	10	0	0	0	0	0	1
27	0	1	0	14	10	0	0	0	0	0	1
28	0	1	0	26	18.6	0	0	0	0	0	1
29	0	1	0	26	18.6	0	0	0	0	0	1

30	0	1	0	0	0	0	0	0	0	0	1
31	0	1	0	0	0	0	0	0	0	0	1
32	0	1	0	0	0	0	0	0	0	0	1
33	0	1	0	14	10	0	0	0	0	0	1
34	0	1	0	19.5	14	0	0	0	0	0	1
35	0	1	0	6	4	0	0	0	0	0	1
36	0	1	0	26	18.55	0	0	0	0	0	1
37	0	1	0	26	18.55	0	0	0	0	0	1
38	0	1	0	0	0	0	0	0	0	0	1
39	0	1	0	24	17	0	0	0	0	0	1
40	0	1	0	24	17	0	0	0	0	0	1
41	0	1	0	1.2	1	0	0	0	0	0	1
42	0	1	0	0	0	0	0	0	0	0	1
43	0	1	0	6	4.3	0	0	0	0	0	1
44	0	1	0	0	0	0	0	0	0	0	1
45	0	1	0	39.22	26.3	0	0	0	0	0	1
46	0	1	0	39.22	26.3	0	0	0	0	0	1
47	0	1	0	0	0	0	0	0	0	0	1
48	0	1	0	79	56.4	0	0	0	0	0	1
49	0	1	0	384.7	274.5	0	0	0	0	0	1
50	0	1	0	384.7	274.5	0	0	0	0	0	1
51	0	1	0	40.5	28.3	0	0	0	0	0	1
52	0	1	0	3.6	2.7	0	0	0	0	0	1
53	0	1	0	4.35	3.5	0	0	0	0	0	1
54	0	1	0	26.4	19	0	0	0	0	0	1
55	0	1	0	24	17.2	0	0	0	0	0	1
56	0	1	0	0	0	0	0	0	0	0	1
57	0	1	0	0	0	0	0	0	0	0	1
58	0	1	0	0	0	0	0	0	0	0	1
59	0	1	0	100	72	0	0	0	0	0	1
60	0	1	0	0	0	0	0	0	0	0	1
61	0	1	0	1244	888	0	0	0	0	0	1
62	0	1	0	32	23	0	0	0	0	0	1
63	0	1	0	0	0	0	0	0	0	0	1
64	0	1	0	227	162	0	0	0	0	0	1
65	0	1	0	59	42	0	0	0	0	0	1
66	0	1	0	18	13	0	0	0	0	0	1
67	0	1	0	18	13	0	0	0	0	0	1
68	0	1	0	28	20	0	0	0	0	0	1
69	0	1	0	28	20	0	0	0	0		

Table A.2: The 69-node radial distribution networks Line data.

Branch code	Node nl	Node nr	R (p.u.)	X(p.u)	1/2 B (p.u.)	Tap	Branch code	Node nl	Node nr	R (p.u.)	X(p.u)	1/2 B (p.u.)	Tap
1	1	2	0.0005	0.0012	0	1	35	3	36	0.0044	0.0108	0	1
2	2	3	0.0005	0.0012	0	1	36	36	37	0.064	0.1565	0	1
3	3	4	0.0015	0.0036	0	1	37	37	38	0.1053	0.123	0	1
4	4	5	0.0251	0.0294	0	1	38	38	39	0.0304	0.0355	0	1
5	5	6	0.366	0.1864	0	1	39	39	40	0.0018	0.0021	0	1
6	6	7	0.3811	0.1941	0	1	40	40	41	0.7283	0.8509	0	1
7	7	8	0.0922	0.047	0	1	41	41	42	0.31	0.3623	0	1
8	8	9	0.0493	0.0251	0	1	42	42	43	0.041	0.0478	0	1
9	9	10	0.819	0.2707	0	1	43	43	44	0.0092	0.0116	0	1
10	10	11	0.1872	0.0691	0	1	44	44	45	0.1089	0.1373	0	1
11	11	12	0.7114	0.2351	0	1	45	45	46	0.0009	0.0012	0	1
12	12	13	1.03	0.34	0	1	46	4	47	0.0034	0.0084	0	1
13	13	14	1.044	0.345	0	1	47	47	48	0.0851	0.2083	0	1
14	14	15	1.058	0.3496	0	1	48	48	49	0.2898	0.7091	0	1
15	15	16	0.1966	0.065	0	1	49	49	50	0.0822	0.2011	0	1
16	16	17	0.3744	0.1238	0	1	50	8	51	0.0928	0.0473	0	1
17	17	18	0.0047	0.0016	0	1	51	51	52	0.3319	0.1114	0	1
18	18	19	0.3276	0.1083	0	1	52	9	53	0.174	0.0886	0	1
19	19	20	0.2106	0.0696	0	1	53	53	54	0.203	0.1034	0	1
20	20	21	0.3416	0.1129	0	1	54	54	55	0.2842	0.1447	0	1
21	21	22	0.014	0.0046	0	1	55	55	56	0.2813	0.1433	0	1
22	22	23	0.1591	0.0526	0	1	56	56	57	1.59	0.5337	0	1
23	23	24	0.3463	0.1145	0	1	57	57	58	0.7837	0.263	0	1
24	24	25	0.7488	0.2745	0	1	58	58	59	0.3042	0.1006	0	1
25	25	26	0.3089	0.1021	0	1	59	59	60	0.3861	0.1172	0	1
26	26	27	0.1732	0.0572	0	1	60	60	61	0.5075	0.2585	0	1
27	3	28	0.0044	0.0108	0	1	61	61	62	0.0974	0.0496	0	1
28	28	29	0.064	0.1565	0	1	62	62	63	0.145	0.0738	0	1
29	29	30	0.3978	0.1315	0	1	63	63	64	0.7105	0.3619	0	1
30	30	31	0.0702	0.0232	0	1	64	64	65	1.041	0.5302	0	1
31	31	32	0.351	0.116	0	1	65	11	66	0.2012	0.0611	0	1
32	32	33	0.839	0.2816	0	1	66	66	67	0.0047	0.0014	0	1
33	33	34	1.708	0.5646	0	1	67	12	68	0.7394	0.2444	0	1
34	34	35	1.474	0.4873	0	1	68	68	69	0.0047	0.0016	0	1

52-Node Practical Radial Distribution Networks Data

This Appendix contains the data for the 52-node RDS used for this thesis project. This networks was also used in [34]. Table A.3 gives the Node data for the 52-node RDS.

Table A.3: The 52-node radial distribution networks data.

Branch code	Node nl	Node nr	Line Length (kms)	Load	
				kW	kVAR
Feeder 1					
1	1	2	3.0	81.0	39.0
2	2	3	5.0	135.0	65.0
3	2	4	1.5	108.0	52.0
4	4	5	1.5	108.0	52.0
5	4	6	1.0	27.0	13.0
6	6	7	2.0	54.0	26.0
7	6	8	2.5	135.0	65.0
8	8	9	3.0	81.0	39.0
9	9	10	5.0	67.0	32.0
10	10	11	1.5	27.0	13.0
11	11	12	1.0	27.0	13.0
12	11	15	5.0	108.0	52.0
13	12	13	3.5	54.0	26.0
14	12	14	4.0	94.0	45.0
15	10	16	1.5	67.0	33.0
16	16	17	6.0	67.0	33.0
17	16	18	5.0	108.0	52.0
18	18	19	4.0	81.0	39.0
Feeder 1					
19	1	20	1.0	108.0	52.0
20	20	21	1.5	94.0	46.0
21	21	22	3.0	81.0	39.0
22	22	23	5.0	108.0	52.0
23	23	24	2.5	108.0	52.0
24	22	25	3.0	102.0	50.0
25	25	26	4.0	41.0	20.0
26	20	27	1.0	108.0	52.0
27	27	28	1.5	162.0	79.0
28	28	29	2.5	68.0	33.0
29	27	30	4.0	68.0	33.0
30	30	31	5.0	95.0	46.0
Feeder 3					
31	1	32	4.0	41.0	20.0
32	32	33	5.0	121.0	59.0
33	33	34	4.0	41.0	20.0
34	33	35	3.5	41.0	20.0
35	35	36	4.0	135.0	66.0
36	36	37	2.5	81.0	40.0
37	35	38	2.0	68.0	33.0
38	33	39	2.5	95.0	46.0
39	39	40	2.0	108.0	52.0
40	39	41	2.5	41.0	20.0
41	41	42	3.0	95.0	46.0
42	41	43	4.5	27.0	13.0
43	43	44	5.0	122.0	59.0
44	41	45	1.5	108.0	52.0
45	45	46	3.5	81.0	39.0
46	45	47	2.5	68.0	33.0
47	47	48	1.5	41.0	20.0
48	47	49	1.5	68.0	33.0
49	49	50	4.0	81.0	39.0
50	49	51	1.5	108.0	52.0
51	51	52	1.0	41.0	20.0

Base kVA	1000
Base kV	11
Line Resistance	0.0086 p.u./km
Line Reactance	0.0037 p.u./km
Conductor Type	ACSR