Various Optimization Algorithms Adaptation and Case Study Applied on Optimal Location and Sizing of Distribution Generation Systems in Electric Power Grids

By

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Abstract

Title: Various Optimization Algorithms Adaptation and Case Study Applied on Optimal Location and Sizing of Distribution Generation Systems in Electric Power Grids

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The development of distribution systems consists in determining the optimal site and size of new substations and feeders in order to optimize the future power demand with minimum investment and operational costs and a suitable level of consistency. This problem is a combination of, non-linear and constrained optimization problem. Several optimization methods, such as genetic algorithms, simulated annealing, hybrid genetic algorithm and variable neighbourhood search have been reported in the literature where several optimization methods have been stated with the uses of the minor structures while the others have extensive solution time.

The main goal behind this thesis is to presents optimization methodologies in the aim to provide a close optimum solution for the (DG) in distribution networks. In the presented methods we take into our account the randomness of distributed generation based on renewable energies, as well as the randomness of electric demand in the planning horizon. First, state-of-the-art research is carried out on existing models for generation planning in electrical systems and distribution network planning models.

A planning model of distributed generation in the distribution networks is proposed with a massive number of studies, which contemplates covering the requirements of the demand in the planning horizon with minimum changes in the existing distribution network. In this thesis the presented methods applied in the aim to provide a better behavior then proposed model as a probabilistic mixing as a hybridization with a genetic operations and extends from a single-objective model, where the main objectives is to optimize the working behavior of the distribution process, technical and environmental impact.

The types of Distributed Generation that are considered are non-conventional, established on sustainable energy sources such turbine energy, photovoltaic energy and hydro-power, as well as storage systems to back up the energy supply in hours of peak demand or to store excess of energy production. The parameters that present randomness are introduced in the model by their probability distributions.

Recent modifications in the electric utility infrastructure have formed opportunity for many technological innovations containing application of Distributed Generation (DG) in order to obtain a maximum achievement. To reach the benefits, factors such as the sizing and the best location have to be considered. This thesis focuses on to define the optimal allocation and sizing of the DG in order to minimize losses and improve the voltage stability in the system. To provide this assessment, several experiments have been made to the IEEE 34-bus test case and various actual test cases with the respect of multiple DG units.and various algorithms were trialled: simulated annealing (SA), hybrid genetic algorithm (HGA), genetic algorithm (GA) and variable neighbourhood search. The Static Voltage Stability Index (SVSI) was used as the objective function for the developed optimization technique and able to minimize total transmission losses, improved voltage stability and increase the voltage profile of the system.

Keywords: Distributed Generation, Optimization, Renewable Energies, Power Losses, Power Consumption.

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Declaration

I, Ahmed Ali , declare that this thesis was self-possessed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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Statement of Copyright

List of publications

- **Journals/Chapters**.

1. Performance of MPPT in Photovoltaic Systems Using GA-ANN Optimization Scheme. Ahmed Ali, Bhekisipho Twala, Tshilidzi Marwala, Springer–Advances in Intelligent Systems and Computing, (Accepted).
2. Electric Power Grids Distribution Generation System For Optimal Location and Sizing A Case Study Investigation by Various Optimization Algorithms, Ahmed Ali, Sanjeevikumar Padmanaban, Bhekisipho Twala, Tshilidzi Marwala, Energies Journal (IF:2.7), (Accepted).
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4. Survey on Techniques and Applications of Solar Energy using Various optimization method. Ahmed Ali, Bhekisipho Twala, Tshilidzi Marwala, Springer– Journal of Optimization Theory and Applications. (IF:1.2), (In Review).

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2. Ahmed Ali, Ilyes Boulkaibet, Bhekisipho Twala, Tshilidzi Marwala.Hybrid optimization algorithm to the problem of Distributed Generation power losses. IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2016.

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Nomenclature

NR:	The number of branches
nb :	Number of bars
GA:	Genetic Algorithms
MOGA:	Multi-objective algorithms with genetic algorithms
ANN:	Artificial Neural Network
LS:	Local Search
DG:	Distributed Generation
SA:	Simulated Annealing
HGA:	Hybrid Genetic Algorithm
VSED:	Variable Search Environment Descending
LP:	Linear Programming
kV:	Kilo Volt
kW:	Kilo Watt
R (Regression R):	Correlation between values
PLF:	Probabilistic Load Flow
EENS:	Expected Energy Not Supported

AUL: The average amount of unloaded load per hour

MCS: Monte Carlo Simulation method

LOLF: Loss of Load Frequency

LOLE: Loss of Load Expectation

HLOLE: Hourly Loss of Load Expectation

LPSP: Loss of Probability of Power Supply

CEL: Cost of Energy Leveled

MSE: Mean square error

RES: Renewable Energy Sources

W1 and W2: weighting factors

$\boldsymbol{\theta}_{\{ik\}}$: Angular opening between the bars and k

$\boldsymbol{P_i(V,\theta)}$ **and** $\boldsymbol{Q_i(V,\theta)}$**:** Net injections of active and reactive power at the bar i

$\boldsymbol{Q_{\{Gi\}} = 0. P_{\{Di\}}}$ **and** $\boldsymbol{Q_{\{Di\}}}$**:** The demands of active and reactive power at the bar i

$\boldsymbol{g_{\{ik\}}}$**, and** $\boldsymbol{b_{\{ik\}}}$**:** Real and imaginary

$\boldsymbol{R_r}$ **:** Resistance of the branch r

$\boldsymbol{I_r}$**:** The current through

$\boldsymbol{IPT_{\{wDG\}}}$ **:** Index line losses considering in DG.

$\boldsymbol{R_k}$: Resistance in line K (p.u / km).

$\boldsymbol{D_k}$ **:** Length in line K (km).

$\boldsymbol{I^2_{\{K,wDG\}}}$**:** Current line k with DG (p.u).

$\boldsymbol{LL_{\{woDG\}}}$: Index line losses without DG.

$\boldsymbol{I^2_{\{K,woDG\}}}$: Online K stream without DG (p.u).

$\boldsymbol{P_{\{Gi\}}}$ **And** $\boldsymbol{Q_{\{Gi\}}}$: Reactive powe.

Chapter One: Introduction

1.1 Background

The need for greater flexibility in the electrical system, the new Legislative and economic scenarios, energy savings and the impact of Environmental, have contributed to the development of Distributed Generation. In particular, the term DG is understood as the usage of generators mounted in the territory close to the loads and connected to the distribution networks, seen fig 1.1. These units may be conventional or unconventional. The presence of Distributed Generation has significant effects on the distribution networks: the presence of bidirectional flows, the increase of the contribution of short-circuit capacity, the impact of voltage levels, the deterioration of the system protections and their coordination and variation of the losses in the lines [1].

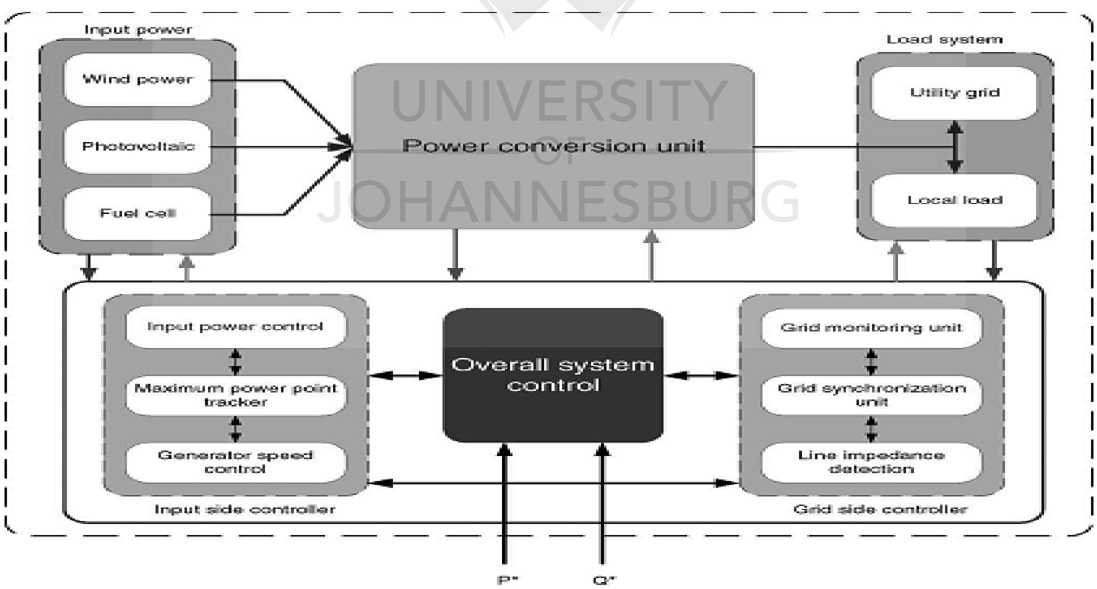

Figure1. 1: General structure for distributed power system having different input power sources[1].

It is clear that a massive and uncontrolled expansion of the Distributed Generation could lead to some of the aforementioned effects, which were not previously foreseen in the long-term planning of the distribution network [2-3]. An in-depth review of the distribution network structure and the control and protection philosophies, as well as a controlled expansion of the Distributed Generation, will allow a more reliable distribution network in the future. The process will be developed in several phases, some of which will be fulfilled in the short and medium term, while others require more time for full implementation [4]. The Important structural changes must be clear to achieve the ultimate goal of transforming the distribution network into a more appropriate design to support the presence of the DG [5].

1.2 Importance of Energy in Distribution Systems.

An electrical power system is constituted by the stages of generation, transmission and distribution, and its main function is to Energy from the generation centers to the centers of consumption in a safe way and with adequate levels of quality. The distribution system has a great importance as mentioned in [6] for its recent applications. It is the part of the electrical system that extends from the distribution substations to the processing centers (primary network), and from there to final consumers (network high school) [7]. These final consumers show a behavior in their demand for electrical energy, in most cases, significantly increasing, approaching with time to the supply limits of the distribution network [8]. Therefore, it is often necessary to expand these distribution systems, specifying the construction and / or expansion of substations, and the installation and / or reconfiguration of new lines, among other measures. For this, it is necessary to plan correctly the modifications to be made. Planning of distribution systems is a decision process that requires the study of electricity supply needs and seeks to identify the best plan to improve the network[9], thus achieving a higher quality of supply at the lowest possible cost.

1.3 Design and Planning of the Distribution System of Electric Power

On the basis of available data on expected growth demand of electrical energy, along with the installed capacity of the network, it is necessary to determine where and in what number new lines, substations and equipment should be located, so that the cost of expansion of the distribution system is as low as possible. In planning a distribution system, in addition to taking into account the cost, the optimum design to be obtained must have highly satisfactory service quality indicators in terms of safety and continuity of electric service.System planners must ensure that there is adequate substation capacity, feeder capacity and acceptable level of reliability to satisfy the power demand forecasts within the planning horizon[10]. These methods can be divided into two groups:

a) Mathematical programming methods
b) Heuristic methods

1.4 Topologies of Distribution Systems

In [12,13] it is indicated that the distribution system more Simple is the so-called simple radial (figure 1.2), which consists of a supply connected to several consumption nodes. Under this scheme [14], it is possible to identify the costs of supplying the energy to each node. In this distribution system if a line fails, the supply of the downstream of the line.

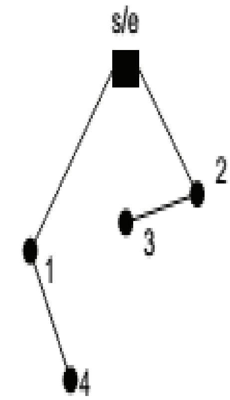

Figure1. 2: Simple Radial System

Another possible type of system is the so-called radial distribution system, which are present when new areas of demand arise at points such as number 3 in figure 1.3.

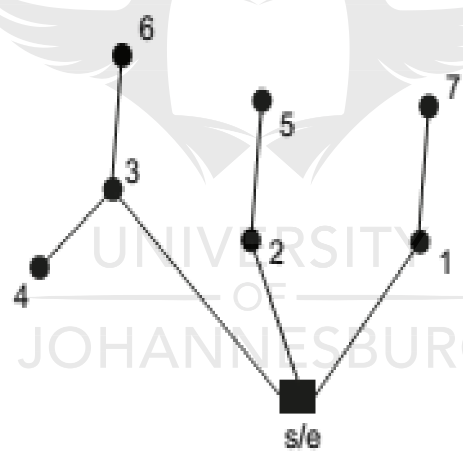

Figure1. 3: Simple Distributed Radial System

A possible third type of distribution system is ringing [15], which is characterized by offering alternative sources of power supply to a particular node, as shown in Figure 1.4. In this case each node is connected to the substation by means of at least two sources and not only to a single source as in the two previous systems. Note that with dashed line, the reserve lines have been represented, in which power will not normally circulate, but which can be operated if necessary [16]. As indicated in their research this interconnected system minimizes the risk of power interruption [17]. Indeed, in radial systems, if the demand exceeds the maximum limit of a line, the supply cannot be realized; while in a ring system there may be the possibility of reconfiguring the network and supplying the power using other lines that were not previously in operation.

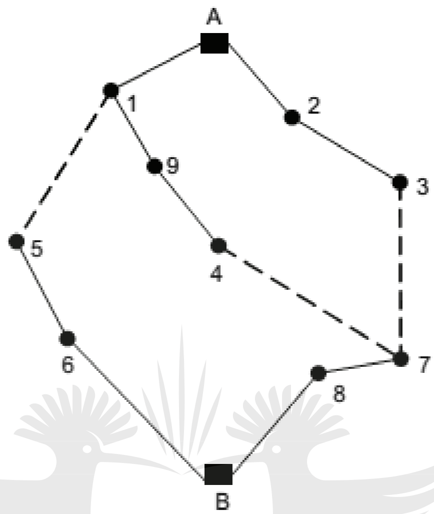

Figure1. 4: Ring distribution System With - - - Reservation Line

1.5 Justification and Motivation

Due to the above situations, it is essential to plan the expansion of Distributed Generation in distribution networks in an optimal way to determine the most economically and technically appropriate options. The investments required for electricity distribution systems to absorb a growing and uncontrolled expansion of distributed generation would be important and accompanied by long periods of return[18,19]. There is an increasing need for the development of planning tools capable of efficiently addressing the growing level of uncertainty that characterizes current generation expansion scenarios in distribution networks. But the economic approach is not enough if we want to introduce desirable goals from a social and even environmental point of view [20]. The decision-maker must take into account in his decisions other factors (environmental impact, emissions, energy price, etc.) [21] that could have the same importance if one thinks about the objective of an electrical or energy sustainable systems development at European level is highly desirable [22].

Consequently, it is understood that the development of planning models of distributed generation in distribution networks based on a mono-objective and multi-objective optimization methodology [23], which take into account the uncertainty inherent in scenarios with high generation penetration distributed based on renewable resources and the risk that all long-term planning entails.

1.6 Optimum Expansion of Distributed Generation in Distribution Networks

The problem of the optimum expansion of distributed generation in distribution networks is to determine the best location of the generators used as DG, as well as the most convenient size, so that the electric power supply and the behavior of the electric network is Minimizing investment costs and operating losses and costs, as long as technical constraints are met throughout the planning period. The problem of optimization is complex, because there is a large number of variables and constraints, in addition to the nonlinearity of the functions of cost and technical restrictions [24,25,26].

Distribution networks, which are generally designed to have a unidirectional flow, i.e. from the substation to the final consumers, are not currently conceived for the Distributed Generation installation [28]. Some studies have indicated that this integration can bring technical and safety problems, which opens the way for the search of the location and mode of operation of the generators that minimize the negative impacts on the distribution [27,29]. Energy is being increasingly used, due to environmental interests, as well as the scarcity of potential energy resources in each country. Wind power has been boosted in recent years, both by governments and by some industries, as it is an energy with a great commercial capacity [30]. In this context, wind energy is expected to have a greater participation in infrastructure and electricity markets. But in turn the primary sources of Distributed Generation based on renewable energies show variability in their performance [31].

1.7 Uncertainty of Renewable Energies

The expansion of the systems in Distributed Generation has reformed a lot in recent years [32]. So far the main focus of support for the planning of the expansion of the generation has been approached from a deterministic approach and very few authors have contemplated the uncertainty in their models. However, risk management and uncertainty management is an issue that still needs to be improved. As further penetration of distributed generation in distribution networks will be likely in the future, it is necessary to start looking for tools to work with the risks and uncertainties of efficient way and, in this way, be ready to exploit the new opportunities that open up [33,34,35].

Renewable generators present randomness due to their primary sources, such as wind in the case of wind generators or solar radiation in the case of photovoltaic generators. But not only renewable energy sources present uncertainty, but also future fuel costs, industry demand, as well as all costs associated with the different materials and equipment used in power grids [36].

1.8 Multi-Objective Optimization Planning Methods

There are few multi-objective methods that have been proposed to resolve the problem of power distribution systems expansion planning with more than one objective function separately formulated. In [40], a planning method is proposed to optimise three objective functions: economical cost, energy not supplied and total length of overhead lines [44]. This method generates a set of Paretooptimal solutions using the s-constrained technique. This technique transforms two objectives into constraints, by specifying bounds to them (e), and the remaining objective, which can be chosen arbitrarily, is the objective function to optimise. In other words, the multi-objective problem is transformed into a single-objective optimisation problem, which is resolved by classical single-objective algorithms[45]. The bounds e are the parameters that have to be varied in order to find multiple solutions. Another planning method that uses the e-constrained technique is reported in [42,43]. This method resolves the single-objective problems using a simulated annealing algorithm.

The disadvantage of the e-constrained technique is that the solution of the resulting single-objective problem largely depends on the chosen bounds E. Some values of E might cause that the single-objective problem has no feasible solution. Thus, no solution would be found. In addition, several optimisation runs arc required to obtain a set of Pareto-optimal solutions.

In reference [46], it is reported a planning method that uses the weighting technique to obtain non-dominated solutions. This technique consists in assigning weights to the different objective functions and combining them into a single-objective function. The Pareto-optimal solutions are identified by changing the weights parametrically with several optimisation runs. One difficulty with this technique is that it is difficult to find a uniformly distributed set of Pareto-optimal solutions [49].
In [47],

1.9 Main Objectives

This thesis analyzes and determines from a technical, economic and social impact perspective for the optimum planning of the expansion of distributed generation in electricity distribution networks. Renewable energies are the main sources of distributed generation, in particular wind energy, photovoltaic solar energy and hydropower. The main objective of the thesis is the multi-period and multi-objective optimal planning of the expansion of the distributed generation in the distribution networks of electric power taking into account the uncertainty of life to the own randomness of the primary resources used by the generation of electricity, as well as randomness of the demand, so the optimization methods are used to determine the different future scenarios within a long-term planning.

The main idea is to minimize the net present value of the asset and operating costs, operation cost, and loads effort of the generators and the distribution network. The model also contemplates technical restrictions of operation such as: power balance in knots, the limits of power of generators, limit of power capacity in lines, limit of maximum penetration of the DG in the distribution network, these methods contemplate the randomness of the variables that represent wind generation, hydropower generation, photovoltaic generation and demand.

1.10 Structure of Thesis

Chapter 1: it justified the importance of electricity distribution, and the factors that in its optimal design, as well as the objectives that are intended to achieve with this Doctoral Thesis, indicating the structure of the same. In addition, the contribution of the research works that have been developed.

Chapter 2. This chapter represents models of ideal development of generation distributed in distribution networks and it reviews literature and publications related to the optimal planning of distributed generation in distribution networks. The review covers optimal models of: planning of distribution networks, integration of storage in distribution networks, distribution network planning with distributed generation, probabilistic and stochastic models.

Chapter 3. This chapter describes the problem of distributed generation planning with a deterministic approach and its integration with storage systems. It presents a number of adopted methods in order to reach optimum DG in the electrical power systems. All the definitions and primary concepts for those methods founded in this chapter. It also shows the mathematical formulation for the adopted methods that allows solve the problem of optimization of energy distribution electric systems.

Chapter 4. This chapter discusses the optimal planning model for distributed generation in distribution networks as a problem of probabilistic optimization. First, the method selected for the solution then it applied in order to evaluate the extracted results.

Chapter 5. This chapter summarizes the most relevant results achieved in this Doctoral thesis, indicating the contributions made in the design and planning of distribution networks. In addition, it indicates the future research work to be carried out, in which will take as a starting point those that have been expressed in this document.

Chapter Two: Models of Optimal Planning of Generation Distributed in Distribution Networks

2.1 Introduction

In this chapter a bibliographic review is made regarding the optimal planning models of generation in electrical systems, emphasizing models related to the planning of Distributed Generation in distribution networks. The review covers:

- Models of optimal planning of distribution networks.
- Models of optimal planning of generation in electrical systems (transmission and distribution).
- Optimal models of Distributed Generation planning in distribution networks, including conventional generators, non-conventional generators and storage.

Based on the bibliographic review, the main features of the revised models are summarized, emphasizing the objective or objectives to be optimized, the optimization techniques used and the technical and economic restrictions contemplated. Finally, the conclusions reached in the chapter highlighting the trend of planning models.

2.2 Models of Optimal Planning of Distribution Networks

Analyze the problem of planning the location, size and service area of distribution substations [51]. The problem formulated considers a linear function of costs directly associated to the lengths of the stretches and is solved by two algorithms; [52,53] to find the shorter routes and from [54] to determine the optimal service areas of the substations. The model allows to solve relatively large size problems, but has limitations of not including the power transport capacity restrictions of the feeders [55].

The use an algorithm for the expansion of the generation in a radial distribution system, which is carried out in two steps. In the first step the concept of minimum expansion tree is used. In the second step the optimization problem is built subject to the technical constraints of the system and integer-mixed linear programming (MIP) is used for its solution [56].

They propose a model based on mixed-integer linear programming to plan the optimal design of a Distributed Generation distribution network where not only operational constraints are considered, but also the best alternative for the location and optimized dimensioning of distributed generators, as well as the selection of generators and optimal routes for distribution lines [57]. It provides a distribution system to minimize power losses in the network [58]. In this model it is crucial to define the size and location of the local generation. Some of the characteristics of the distribution systems are considered, such as: radiality structure, number of nodes and the range of the relation [59,60]. In this thesis, a loss sensitivity factor, based on equivalent current injection, is formulated for the distribution system. The sensitivity factor is used to determine the optimal size and optimal location of the DG, as well as to minimize power losses by an analytical method, without the use of the admittance matrix, the inverse of the admittance matrix or the of the matrix. It is shown that the proposed method is in accordance with the classical algorithm based on successive load flows [61].

To present an algorithm to obtain the optimal location of generators that allow the proper operation of a distribution network where Distributed Generation is included [62]. The proposed algorithm has been developed for electric power distribution systems and is based on the heuristic technique known as tabu search [63]. The objective function to be optimized is the minimization of the cost of generation with penalties due to overloads in the branches and voltage drops in the buses. The technical restrictions are of operation and control variables [64,65].

2.3 Models of Optimal Planning of Distributed Generation in Distribution Networks

To propose a structure to optimize the planning of distributed generation emphasizing the risks and uncertainties, taking into account technical, environmental and commercial aspects due to legislative changes, fuel prices and technological innovations [67].

Also present a method for the evaluation and minimization of network costs with distributed generation. The tools for optimizing the network are to realize the integration at a cost efficient in the long term [68,69]. The long-term planning of medium voltage distribution networks is based on a rural approach, with a horizon of several decades [70]. Planning is carried out taking into account geographical constraints such as location of substations and routes in bad use, in addition to technical restrictions: supply and load of the consumers, maximum amount of equipment and operation under normal conditions and under failure, permitted voltage limits and short circuit currents are considered, among others [71]. The objective of planning is to minimize the cost of investment and annual operating costs as well as the costs of power losses. In this contribution, a computational tool is used, which is based on a two-stage heuristic method that considers all technical and geographical constraints. In the first stage an initial solution is generated with an algorithm originally developed to solve the problem of the vehicle route, and then it is improved with a method based on a tabu search [72].

To employ a methodology based on an optimal optimum flow model, using linear programming [73]. The optimization process is used to reduce the environmental and economic impacts, taking into account the installation of combined cycle plants, wind plants, biomass exploitation together with combined industrial and heat systems [74]. This model describes the energy system as a network of energy flows, combining the extraction of primary fuels, through conversion and transport technologies, to meet the energy demand of a high consumption of materials [75].

Planning horizon is defined by periods, usually of different size. The objective function is to minimize the cost of the conversion of the primary energy over a selected time horizon [76]. The constraints of the model must satisfy the peak demand of electricity in all periods plus a considerable margin, in addition to contemplating the exported energy. The limits of each generation source must be considered so that annual energy production is not exceeded [77].

To propose a method of optimization for the planning the expansion of a sub transmission network in the medium and long term of a sub transmission network. The optimization technique used is mixed-integer nonlinear programming. The objective function minimizes the total costs obtained from the sum of the investment cost, plus the operating costs.

Also propose a new methodology to determine the optimal location of generators distributed [78]. The objective is to maximize the generation subject to the restrictions of percentage of penetration of renewable energies imposed by the European Union as part of the strategy of the Kyoto Protocol to reduce the greenhouse effect [79]. The objective function is maximized subject to restrictions, such as: the current in the lines does not should exceed its maximum capacity, the amount of generation should not exceed the range of the transformers to its highest voltage range, the short-circuit capacity should not exceed the capacity levels of the equipment, the short-circuit range of the generators must be according to the short circuit level of the buses close to each generator, the power of the generator on the bus where it is installed must be less than the available power of the resource and greater to the installed power. Linear programming is used to determine the optimal location of the DG [81].

A method to regulate the voltage in a radial distribution network with the Distributed Generation installation is presented by [82,83]. A voltage drop compensator is used in the interconnection lines between the distribution network and the Distributed Generation, which allows the voltage to be maintained within previously established levels by operating the tap changer of the main transformer [84].

The voltage level of each Distributed Generation system can be autonomously and decentralized to carry out the coordination of the voltage regulation system of the complete distribution system. It uses the optimal load flow model, based on linear programming to evaluate the production contribution and Distributed Generation efficiency [85]. The objective function to be optimized (minimized) includes costs due to the production of energy in the presence of technical constraints and energy policies. Another study shows the behavior of fuzzy methods [86] presents an adaptive fuzzy genetic algorithm as a possible implementation for any radial type distribution system [88]. The algorithm is developed in three stages. The first stage comprises an appropriate location and dimensioning of the substations using load flow, which allows to know the voltages at the nodes and the total losses of active and reactive power [87].

In the second stage heuristic rules are used created on the effects of the simulation of the flow of charges of the first stage, an appropriate number of lines and their corresponding knots are found. In the third stage the reconfiguration of the network is obtained so that the general structure remains radial and all the nodes are energized [90]. A loss minimization plan and a cost minimization plan are used to minimize the losses of active power and achieve a minimum cost that includes the cost of investment and the variable cost.

To applies the Tabu Search technique to find the optimal location of distributed generators from the point of view of loss minimization [91]. The purpose of this research is only to provide information about the size and correct location of the Distributed Generation, to know the amount of losses that would be reduced. It is assumed that the size and quantity of the generators are known, as well as the characteristics of the loads, which are evenly distributed throughout the distribution system [92,93].

Also present a method for planning the expansion of generation, reconfiguring the network and constructing new generation plants [94]. The method considers a natural growth of the demand and installation of older customers. The method first attempts to reconfigure the network objective by "switching" (open or closed) to minimize losses and analyzing network security through a contingency analysis. If operation restrictions are violated when the network is reconfigured, then the method attempts to construct candidate generation plants.

2.4 Integration of Energy Storage Systems

The supply of energy in distribution networks from primary sources is not constant and seldom coincides with the pattern of consumer demand. Electricity itself is difficult to store in significantly large quantities. Secondary energy storage is necessary for more efficient use of existing generating capacity and for allowing more consistent use of renewable energies, which tend to provide power intermittently. The lack of storage in fact has been cited as a barrier to the substantial introduction of renewable energy sources in the grid [95].

To describe a model to solve the optimal flow of power in a power system, which includes wind farms and hydraulic storage units belonging to independent power producers [96]. When independent producers are present in the system, the operation of wind farms and hydraulic storage units must be under contractual agreements of purchase and sale of energy between each producer and public generators [97]. The optimum coordination of renewable energy sources is also examined in order to optimize their exploitation.

The objective function to (minimized) is the operating cost, which is the sum of the operating costs of the conventional generation sources plus the cost imposed by the operation of the independent producers, subject to power balance restrictions, both of reactive as of active in each node of the system, control of the limit of the variables, as well as limits of security. Other restrictions are included in the model, as is the penetration limit of wind energy. All variables are linearized to obtain a linear model. The model is solved by a Simplex algorithm using routines provided by the IMSL mathematical library.

To perform the optimization of a distribution system where it is considered DG, in which conventional generators and non-conventional generators are proposed that have random characteristics, in addition they are considered storage units to support the periods in Unconventional generators are not present. The model is optimized using an optimization package that uses linear programming (LP) [98]. The minimization of the rate of installation of the conventional sources associated to the generation capacity plus the cost of operation and maintenance associated to the cost of energy; the fixed costs of renewable sources are also included in the objective function.

Variable costs of renewable sources are not considered, because they assume energy with negligible operation and maintenance costs. Costs are considered fixed lines of distribution lines plus fixed costs of storage units. The restrictions considered are: 1) Balance of power in the knots. 2) energy balance constraint, where storage units take charge during periods when renewable sources are present and are discharged in periods when renewable sources are not present; 3) restriction of capacity limits of conventional and renewable generators, as well as capacity limit of distribution lines.

It uses average hourly values of demand, wind speed and solar radiation. To present a model for the optimum location of storage systems where there is a high penetration of wind generation [99]. The proposed methodology is based on the storage of excess energy produced by wind generators, which serves to minimize the annual energy cost. The goal of energy storage for this site is to seek the economic benefit to independent owners, so they must properly dimension the amount of energy exceeded by wind generators to be stored. Methods of forecasting demand and wind generation are used to know with some precision both the demand and the supply of energy produced annually.

2.5 Probabilistic Models of Optimal Planning of Distributed Generation

For many years the load flow solution has taken known represented input parameters. Any change in input values requires a new load flow solution. Consequently any uncertainty and random variation due to errors in the forecast, generator outputs, etc., were not reflected in the flow results of loads. An analytical alternative that has achieved remarkable interest is probabilistic load flow (PLF).

To presents a Monte Carlo Simulation-based technique to show the effects of nonlinearity on the network equations and the assumption that a normal distribution for the random variables is completely reliable. The algorithm used is new for probabilistic load flow. They perform a review of publications related to probabilistic techniques for evaluating the reliability of electric systems [100].

A probabilistic reliability model for a radial system with low rates of load variation is presented by [101]. Firstly, the improvement of reliability indicators, specifically the Expected Energy Not Supported (EENS), is calculated by means of line reinforcement and addition of substations. Then the methodology determines the equivalent of conventional DG to be installed as a service to reach the previously calculated reliability indicators, maintaining the given load requirements. In this methodology it is assumed that the location of the DG is not relevant [102].

The generations mentioned above are dispatchable. The inclusion of non-dispatchable generations, e.g. Distributed Generation, in the interdependence model. The interdependence between load demands and non-dispatchable generations are modeled through two levels, for example in the time of day or station, and temperature. These two levels have the interdependence due to the cyclical phenomenon (day, week, season) and the random phenomenon (temperature, cloudiness,Wind) related to the demand for cargo and non-dispatchable generations. The modeling of Distributed Generation interdependence, for example, generation of wind farms, is of great importance because the wind generators are correlated with adjacent wind farms, due to the similar velocity of the area [102].

In [103] they use sequential Monte Carlo simulation to evaluate the reliability of a system that has conventional units like DG. The total power of all active DG units is treated as a random process due to the random nature of the performance of the DG, i.e. failure rates and reset times [104]. The operation of the DG is represented as a two-state model. The operating cycles of all DG units are combined to obtain the capacity availability curve of the DG.

Next, the DG availability curves are added to the centralized generation capacity curve to obtain the total available generation capacity curve at each hour. Subsequently, the average amount of unloaded load per hour (AUL), which is obtained by the Monte Carlo Simulation method (MCS), is calculated for a large number of annual samples. Based on the results, it is concluded that with the implementation of DG, the value of AUL decreases considerably. In addition, the capacity of the distribution system can be improved in case the load is increasing. Load modeling should be divided into: 1) short-term modeling, which takes into account the uncertainty of social and environmental factors in the planning of the operation, and 2) long-term modeling of the load , Which takes into account the uncertainties of demographic and economic factors in long-term planning. Short-term load modeling picks up the daily peak values of a substation every two months. Long-term load modeling collects the annual peak demand values observed in a substation for a number of years, then a PLF is carried out to obtain the system states using linearized load flow equations [105].

The power flows in the lines are obtained from the system states using the classical nonlinear load flow equations. In addition to the adequacy of the previous indices, the results of the PLF simulation provide more points of view than the conventional deterministic study, As an alternative to increase the support of reactive power generation instead of the construction of a line. In [106] discusses the short-term planning of a distribution network to take into account the stochastic behavior of the Distributed Generation units. The results of the simulation show the ability of the statistical planning method to increase the transfer capacity of the network compared to the traditional worst case planning principle [107].

Stable and when operating in load-tip trimming mode. According to the results obtained, it is observed that the operational cost using the hourly valuation of reliability is significantly lower than the operating cost using the average annual cost of operation [108]. From this it is concluded that the cost of hourly interruption is an important index of reliability in the determination of the strategy of optimal operation of the DG.

The effect of fluctuation in the power output of the generators was included by modifying the generation model of the non-conventional unit. The LOLF (Loss of Load Frequency) and LOLE (Loss of Load Expectation) values were calculated for one hour and combined in the generation system models, where each sub-system was treated as a multi-state unit. Subsequently, the cumulating algorithm was applied to combine the subsystems and obtain the HLOLE (Hourly Loss of Load Expectation) total of the system [109].

The results obtained using the proposed method show a decrease in the values of the reliability indices for low penetration levels. For a high penetration the effects of the fluctuation of the output power begin to be significant and the high availability of unconventional units is surpassed by the variability in the output. Another way of calculating reliability indices is to use sequential simulations, with this approach Wang and [110] present a sequential simulation in time to evaluate the reliability of the distribution system with wind generations.

The power delivery of the wind generator at a specific time is expressed as a function of the wind speed and the generating capacity of the unit. A six-state model is developed to consider the simultaneous effects of wind speed and forced WTG output. A two-state model represents the other components of the distribution system. It is observed that the reliability varies in each individual point of load depending on the location of the load node in the network, the topology of the protections and the level of load.

In addition, it is found that by selecting the optimal WTG number with a specific location (according to wind conditions), the distribution system can be substantially developed. In [111] show a novel procedure for the optimal location of wind generators in a wind farm, based on Monte Carlo Simulation. The model maximizes energy production and minimizes the cost of installation. As a case study a site is divided into 100 square cells where the installation of wind generators may be possible. To optimize (minimize) the total cost, the investment cost is modeled so that only a certain number of necessary wind generators are considered [112]. The results obtained by the Monte Carlo simulation method are compared with the solution given with a heuristic technique named as genetic algorithm (GA), obtaining better results.

To develop a model to optimize the dimensioning of a hybrid solar-wind system together with storage, so that the system can work in optimum conditions with optimum configurations of the investment requirements and reliability for the demand of the load [101]. In this work, the model uses an optimization tool that is based on the loss of probability of power supply (LPSP) and the concept of cost of energy leveled (CEL). Therefore, the objective function is based on LPSP so that the system configuration obtains the required reliability.

To present an analysis to determine which are the most appropriate energy sources that must be installed to carry out the expansion of the generation in a certain area, as well as to determine in what period of time these sources must be in operation. A deterministic methodology is used to know the capacity requirements in planning. These techniques associate hybrid generation and cannot be extended to include photovoltaic sources or wind sources that have high levels of fluctuation of capacity [113].

The number of random variables and system complexity increases when renewable energy sources are included. The simulation algorithm first compares the load level of the system with the capacity of the photovoltaic subsystem and all dispatches available in this interval. The remaining load is distributed between diesel and wind systems in a range specified by restrictions imposed on problems of stability of wind energy sources, always "dispatching" wind energy to allow maximum penetration. The developed method uses Monte Carlo Simulation.

It shows a mathematical formulation to determine real-time electricity costs. Time series prediction models are used to investigate the impact of wind power on electricity market prices [114]. It is carried out the configuration of a network composed of 6 buses of a transmission system and 3 buses of a distribution system. Generation units are assumed to operate under the same wind speed conditions. The distribution system is connected to the transmission system by means of a lifting transformer. The model is implemented with the GAMS optimization software. The problem is formulated as a nonlinear programming problem and solved using the MINOS solver. In particular the wind turbine models were implemented in MATLAB®. The MAE prediction tool is used for predicting energy prices.

2.6 Stochastic Models of Optimal Distribution Network Planning with Distributed Generation

Stochastic optimization is used to deal with problems with data and variables with uncertainty, such as wind generation or solar radiation. To formulate a stochastic optimization model to solve in the short term a problem capable of taking into account the sources of wind generation, which are non-dispatchable and are also variable in the electric market environment [115]. The main benefit is that when the worst deterministic scenario is compared, a large penetration of wind power is allowed without sacrificing safety. The objective of the problem is to minimize the expected social cost. The technical restriction adopted is the maximum penetration of wind generation, which ranges from 10% to 20%.

(Haesen and Driesen 2007) present a robust planning methodology for the integration of generators in distribution networks. The methodology is based on the improvement of the precision of the Monte Carlo Simulation nested in a multiple evolution algorithm. The objectives pursued are to evaluate the appropriate trade-offs with respect to technical and economic aspects.

It present a problem of planning expansion of the long-term generation of a transmission system. The model considers losses and ensures optimum convergence [116]. The model approach uses mixed-integer linear programming (MIP) for the solution. The model is applied to "Garver's 6-bus system", "the IEEE Reliability Test System" and to a Brazilian real system. The results show the precision and efficiency of the technique used. The set of constraints includes, among others, dynamic constraints on investment and operating cost variables, as well as nonlinear and convex static constraints [117].

Due to this inherent complexity and the lack of computational tools the transmission expansion problem is made in two simplified models related to dynamic and stochastic aspects. The objective function represents the sum of the investment cost of new lines and the cost of operation of the generation units. A single demand scenario is typically considered to correspond to the maximum demand of the horizon considered. Also considered are power balance constraints on the power knots injected at each node, as well as operating restrictions of the generators [79].

Uncertainty in demand forecasting is currently a problem in planning the expansion of generation. They use a decomposition strategy called the Lagrangian relaxation technique for a stochastic optimization structure. A scenario tree is constructed where costs are attributed to each node of the tree [118]. In each iteration for each generator a sub-problem has been solved, which consists in minimizing the average cost of generation on the tree of cost scenarios. An optimization deterministic model is carried out on a daily scale with a detailed model of operating restrictions.

To present a method whose approach is the analysis of the operation of Distributed Generation customers under an uncertainty perspective [119]. A random state transition procedure is used to cover all possible operating scenarios of the system. The new structure of the system may include, in addition to the main components, different Distributed Generation technologies in different locations and schedules. The time series simulation is used to represent the randomness of the operating cycles. A two-stage model (high position and low position) is used to simulate the operating cycles using a code in MATLAB.

Some of the problems that currently exist in systems Electric power are the violation of limits and maintenance of all Security systems. This situation is described as a state of emergency, and the actions required for its correction are called actions to control emergencies or corrective control actions.

Emergency does not necessarily mean an immediate collapse of the system, but it is an action that requires immediate correction. Corrective Action is one of the actions that should be taken into account.

They also presents a solution for the optimal restoration of the operation of the power system for different operating conditions. operation. Genetic algorithms (GA) are applied to carry out this optimization [120]. Three different procedures based on optimization Multi-objective algorithms with genetic algorithms (MOGA) are used to optimize corrective control actions: The first procedure is based on a switching of the transmission lines and re-dispatch of the generation. The second procedure is used to determine the location and size of the Distributed Generation, while the third procedure is used to solve the problem of unbalanced loads and generation using load disconnection.

To apply the fuzzy set theory in multi-criteria decisions, which was first used by Bellman and Zadeh. In this study a two-phase procedure is used to solve a multiobjective problem of diffuse linear programming [121]. The procedure provides a practical solution approach, which is an integration of diffuse parametric programming and diffuse linear programming. The interactive concept of the procedure is performed to arrive at simultaneous optimum solutions for all the objective functions for the different degrees of precision according to the preferences of the decision maker. In the first stage of the procedure, a family of vector optimization models concession). The solution of the best planning scheme between the Pareto set is made using Monte Carlo Simulation under uncertain situations. The technologies of DG that are considered are: conventional and renewable, photovoltaic, wind, fuel cells, micro turbines and gas turbines. To evaluate the effectiveness of the proposed method, a distribution system is used to plan the expansion of generation under two scenarios with environmental impacts.

In the multiobjective optimization model used in [122] we consider the optimum size and location of lines and substations, as well as the of the design (monoetapa or multistage) and the corresponding restrictions techniques. The optimum multiobjective design of distribution systems is carried out using an Evolutionary Algorithm, using an optimization model of non-linear programming that incorporates the simultaneous optimization of the economic costs and the reliability of the distribution system, using the real nonlinear variable costs Associated with such a system. The optimal multiobjective design model used allows obtaining a broad set of non-dominated solutions (economic cost and reliability) from which the designer can select those that, considering several factors, consider of greater interest.

Then they provide a modified Genetic Algorithm is presented that allows determining the optimum indexes of the reliability of the constituent components of a distribution system, minimizing the annualized total cost. The proposed algorithms apply to a secondary substation of the Taiwan Power Company. The results confirm that with the proposed Genetic Algorithm it is more likely to obtain the overall optimal solution than with the conventional method. The proposed method is useful both to modify or extend existing systems and to plan new systems. The objective function includes the total cost of the interruptions, the cost proportional to the loss energy, the cost of modifying the reliability and the cost of the total number of devices in the system.

To present a multiobjective optimization methodology for the island of Lesvos in Greece, where several renewable energy sources could be exploited to meet some of the economic needs of the island [124]. The criteria to be met are: environmental impact, demand, cost, and resource constraints. The study poses two objective functions: investment cost and environmental effects. The two objectives to be minimized are in conflict, since when the cost decreases the system operates increases the generation with conventional sources and the emissions produced by them increase. The obtained results give the possibility of the designers of the system can select the best option according to the needs and existing regulations. The constructed mathematical model indicates that wind generators can be used to cover electrical demand and solar collectors can be used to meet hot water needs. While geothermal energy and biomass can be used to cover a percentage of the demand for heating. They show a holistic design and planning method particularly for integrated energy systems, which include a large number of parameters. The method allows quantifying economic and ecological parameters by comparing solutions. An optimal representation of the Pareto curve provides a view of the best solutions which is determined using an efficient multiobjective algorithm. The results of the case study of the isolated system always show favorable solar conditions, solutions including solar thermal or photovoltaic production. The proposed method allows an easy evaluation of the sensitivity of the solutions by changing fuel prices.

To present a new probabilistic model based on Fuzzy sets for multiobjective planning of distribution networks. The model determines optimal location and dimensioning. A meta-heuristic algorithm based on Tabu search is used. The model also allows determining the optimal reserve of the feeders that provide the best reliability at the lowest cost in the distribution network. The multiobjective feasible model provides solutions that simultaneously: minimize cost, maximize reliability and minimize the risk of exceeding capacity limits [125].

Allowed power of the feeders and substations, as well as the risk of exceeding the permitted limits of voltage drop in the network nodes. Also, a fuzzy feasible multiobjective model to determine the optimal location of Distributed Generation for loss reduction and improvement of voltage profile in electric power distribution systems. The multiobjective problem is developed in two stages. In the first stage the set of non-dominated planning solutions is obtained, using genetic algorithms. In the second step, a solution of the set of non-dominated solutions is selected as an optimal solution using an appropriate maximization-minimization approach. The input parameters are modeled using the fuzzy set theory to use them in the diffuse power flow, which gives us a real view about the future demands of the distribution system because this model considers uncertainty of future points.

2.7 Conclusions

In the review of the models, the characteristics of each model are collected, such as: objective functions or functions to be optimized, technical constraints, economic constraints, social constraints and optimization techniques used to solve the model. The introduction of DG presents a set of new conditions in the network and consequently the appearance of new technical problems that must be studied when considering the DG connection. In the revision of the planning models of distribution networks, in which DG has been installed optimal location of DG.

- Optimal Dimension of DG.
- Optimal selection of lines.
- Expansion of generation to different horizons.
- Stability of electrical power parameters.
- Reliability of the network.

Chapter Three: Adopted Methods in the Optimization Process for Optimal Distribution

3.1 The System of Distribution of Electrical Energy

The electric power systems are structured in the generation, transport and distribution parts, hierarchical as shown in Figure 3.1. The generation takes place in the power plants that, depending on the type of primary energy used, can be of several types (hydraulic, thermal, wind, nuclear, solar, etc.). Electric power, in the case of large power plants, is transported through the high voltage lines (transport network). The normalized values for the tension of the transport lines are 132, 220 and 400 kV.

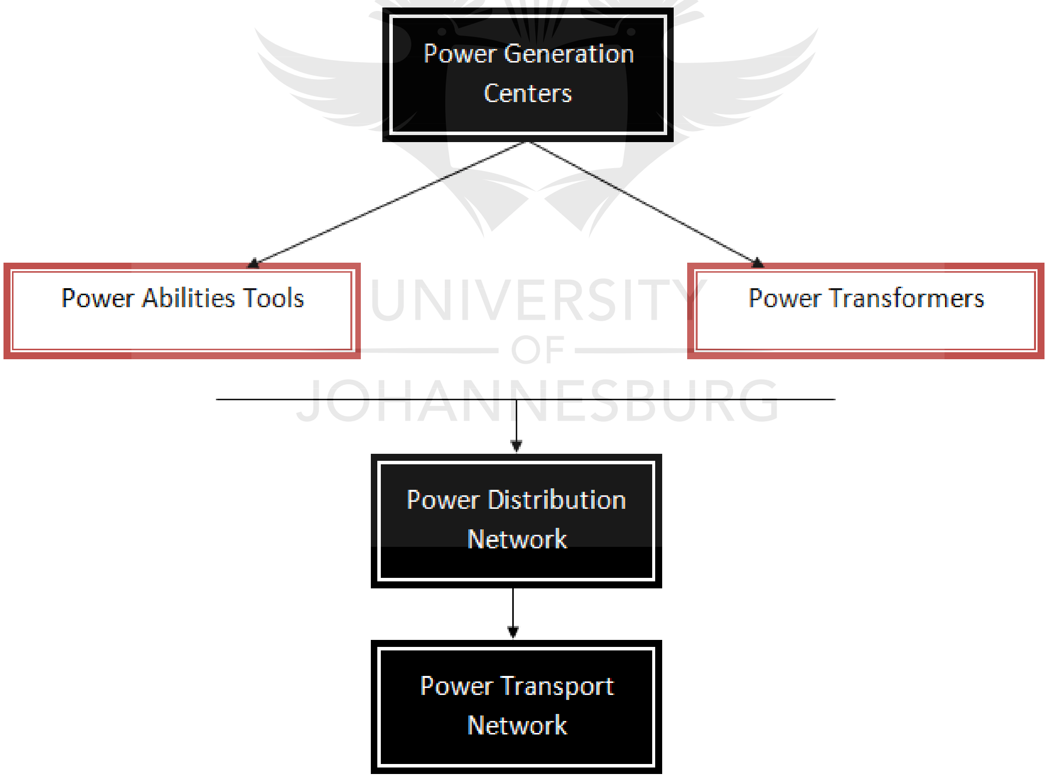

Figure 3. 1: Power Distribution Process

The distribution of the electric energy from the substations of transformation of the transport network is realized in two stages. The first is constituted by the distribution network, which, starting from the transformation substations, distributes the energy

Usually by means of rings that surround large consumer centers, until reaching distribution transforming stations. The voltages used are between 25 and 132 kV. Intercalated in these rings are the distribution transforming stations, in charge of reducing the voltage from the distribution level to the medium voltage distribution. The second stage is the distribution network proper, with operating voltages of 3 to 30 kV and with a very radial characteristic. This network covers the area of large consumer centers (population, large industry, etc.), linking transforming distribution stations with transformation centers [52].

Urban distribution networks are usually characterized by high load density, usually using underground and fully meshed networks, with a large number of backup feeders in order to increase the reliability and security of the electric power supply, the operation being radial. Rural distribution networks, in which airlines are almost always used, usually have a radial structure, with a main feeder (trunk) from which other lines is coming out.

3.2 Introduction to Optimization

Optimization consists of selecting a better alternative, in some sense, than the other possible alternatives. In general, optimization is divided into three broad areas: classical mathematical techniques, heuristic techniques, and the combination of both.

To apply a certain optimization technique it is necessary to have what is called the mathematical optimization model. A mathematical optimization model is composed of [37]:

- Objective function: It is the quantitative measure of the operation of the system that you want to optimize (maximize or minimize).

- Variables: They represent the decisions that can be taken and that modify the value of the objective function.
- Restrictions: They represent the set of relations (expressed through equations or inequalities) that some of the variables must satisfy.

Thus, mathematically an optimization model can be as min/ max f(x) expressed as:

$$g(x) = 0, h(x) \leq 0, p(x) \geq 0 \qquad (3.1)$$

There are some types of optimization problems that can be classified according to the type of variables and the properties of the objective functions and constraints min/max f(x). From the classification shown in table 3.1, below we will comment on those types of problems that are of interest for the research works developed in this doctoral thesis.

Table 3.1. Classification Appearance

Appearance to consider	Type of optimization problem
Domain of variables	Keep going Whole Mixed
Existence of restrictions	Restrict Unrestricted
Linearity of functions	Linear Nonlinear
Number of objectives	Mon-objective Multi-objective
Availability	Short term Medium term Long term

Within the mathematical methodologies available to solve the problems of optimization, we find the linear programming, whole, mixed, nonlinear, stochastic and dynamic. In addition, there are heuristic techniques, adequate when the mentioned techniques are not able to solve some optimization problems correctly.

Given the time horizon, it is possible to speak of static models, where considers that time does not fundamentally condition the optimization of the system, being the results that are obtained valid for a determined year or for a determined situation in the horizon of study [94]. On the other hand, the dynamic models obtain several solutions, each of them corresponding to different temporal moments that are between the initial instant that is considered and the determined time horizon. Another aspect that can be considered when proposing an optimization model is that of uncertainty. Uncertainty, in the optimization process, can be stochastic or deterministic. The first refers to the one in which it is not feasible to attribute a rational behavior model to it while in the second it is possible to determine (strategy).

3.3 Planning of distribution networks

There are three types of design and / or planning of energy distribution systems (Peco, 2001):

(i) New construction.
(ii) Expansion
(iii) Operation.

In this research the main objective is to obtain feasible solutions in systems belonging to the second type, in which it is desired to optimize a network in a certain period (static) and expand the distribution system over time (dynamically) to optimally satisfy the increase in the number of consumers and demand.

The objectives of distribution network planning may vary considerably from one installation to another and from one plan to another. However, it is possible to formulate common objectives for planning tasks in general, as shown in Figure 3.2.

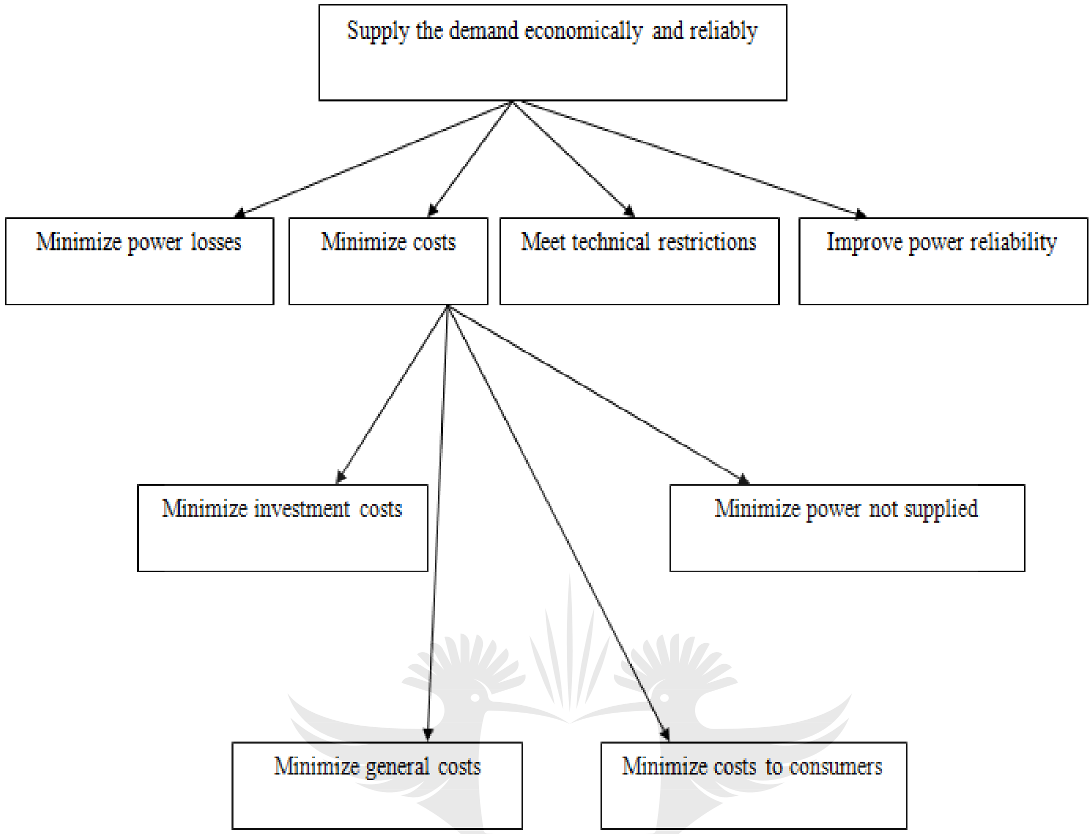

Figure 3. 2: Hierarchy of objectives in the design of distribution networks

For example, consider expanding the capacity of existing substations and changing the sections of the drivers. In addition, some of the objectives can be considered as restrictions. In this Doctoral Thesis, following the works that can be found in [22], it is intended:

- Obtain a technically feasible solution, complying with the maximum permissible voltage drops as determined by the company's policy without exceeding the capacity limits of the drivers.
- Evaluate the cost of each line and each substation in the system.
- Ensure that different types of costs can be compared. This requires that the costs of the different technical solutions proposed should be evaluated in monetary

units referring to a certain moment in time. To this end, the annual costs and capital invested in the distribution system are calculated at the present moment

3.4 Static or single-stage and dynamic or multistage planning

It is necessary to define, in the planning process of the distribution networks, what the planning horizons are in order to obtain the network that minimizes the total costs under certain constraints. When considering a single period, the distribution system should be determined considering that the present value of the total cost of investment and operation is the minimum for the considered period of time, usually one year.

Static model: A single stage, single-stage, is considered, and in this model, the demand of each consumer does not change during the period (or in a single stage) or dynamic (of several stages) study. Dynamic model: Several stages are considered, multi-stage, and the aim is to obtain the optimal design for each of the different stages in which the study period has been divided.

In the single-stage planning it is assumed that all investments are made in the same instant of time. The problem of multi-stage planning of the DG is composite than the one-step planning because the electricity networks evolve with time with an uncertain growth of the demand of electrical energy. The planning period, which corresponds to the economic life cycle of the equipment, can be divided into several sub periods. Note that two sub periods have been designated as the decision-making period and the estimation period. The duration of the sub periods can be variable. In the initial phase of the distribution network planning process, the current capacity of the system is analyzed with short-term demand requirements. The aim is to ensure that

Consumers receive the energy demanded with the requirements of normalized voltage drops, radiality and energy balance. The result of short-term planning is a set of decisions such as location and capacity of substations, capacity and section of the drivers.

The planning period and the decision-making period have a commonality in the beginning. The time interval after the decision-making period until the end of the planning period is the so-called estimation period or the medium- and long-term period. The objective of this stage is to ensure that the decisions made during the decision-making period are adjusted within the long-term requirements and therefore satisfy all constraints and contribute to minimum and minimum planning Energy not supplied (as it has been considered in this Doctoral Thesis). In this period the dimensional aspects of the network are defined.

Note that the changes made to the electricity distribution system in the short-term period are part of the long-term solution. This results in a multi-stage approach, where in addition to the short-term period, there may be additional periods. To apply this approach, this thesis proposes novel methods appropriate for this purpose as optimization techniques.

3.5 Basic Methodology Algorithms

In the last decade, there have been profound changes in the electricity sector. Within these changes participations increased of generation distribution (DG) on distribution networks is highlighted. This phenomenon has been driven by several factors including: new technological advances in the production of electricity on a small scale, preference for the use of renewable resources, difficulties in network expansion and a growing interest in incorporating demand and active agent in the electricity markets [18]. DG (defined as production of electricity close to consumption centers) can contribute to reducing losses, improving voltage profile, improved reliability and postponing investments and transmission distribution [78]. However, as noted in [51], harnessing the benefits of DG depends largely on its location, sizing and network features. That is why in the last decade have explored different methodologies for proper location and sizing.

In [6] a literature review of the techniques used for the location and optimal sizing of DG in distribution networks is presented. The authors classified the techniques in analytical methods, metaheuristics, and mathematical programming. It should be noted that for the problem under study metaheuristics techniques have significant advantages over classical mathematical programming because of the nonlinear nature and not convex on the DG. On the other hand, the main weakness is that metaheuristics do not guarantee obtaining a global optimum. However, possible to find a solution or set of high quality solutions. Another advantage lies metaheuristics techniques is that they allow the use of more detailed models of network operation as the AC model. In contrast, to apply mathematical programming techniques to the problem of optimal location and sizing of DG you need to use linearization or approximations to the equations in the balance of power.

Metaheuristic optimization techniques have been widely used in the location and design of the DG. Among these are genetic algorithms, tabu search and colonies of particles. In [1] a model of multi-objective optimization is presented to determine the location and optimal sizing of DG using the technique of simulated annealing. The objectives are modeled power losses, the number of generators, the voltage profile and power injected by the DG. In this sense, it seeks to find a solution that would increase the voltage and reduce losses to the minimum DG units in the system.

In [13] the authors present a population-based metaheuristic parasitic reproductive behavior of some species of cuckoos (Cuckoo Search Algorithm) for the location and optimal sizing of DG. The advantage of this algorithm is that it requires a few parameters to calibrate. The aim of the study is the reduction of active power losses. Hybrid methods combine two or more search techniques in order to exploit the potential of these and compensate for their deficiencies. The most common methods combine population hybrid techniques with methods that enhance some kind of local search or alternatively, heuristic methods with classical mathematical programming.

In [36] a combination of simulated annealing and genetic algorithms for optimal location of DG. The proposed objective is to minimize losses. The authors show that the combination of GA with simulated annealing proves more effective using only GA. In [61] The proposed model simultaneously optimizes two objectives: the benefits of the Distribution Company and owner of the DG. It also considers the uncertainty of demand and energy prices. In [43] a hybrid algorithm that combines particles gravitational colony search to determine the proper location and sizing of the TG that minimizes loss occurs, improves stress profiles and reduce emissions.

The aim of this doctorial thesis is to contribute the discussion on the effectiveness of heuristic and metaheuristic methods for optimal dimensioning and location of DG. To this end, we have implemented and compared four different techniques i) Simulated Annealing ii) Variable Search Environment iii) Genetic Algorithm and iv) a hybrid method that combines Variable Search Environment with a Genetic Algorithm also Given the multi-modal nonlinear intrinsic nature (multiple local optima) and non convex problem of optimal location of DG, metaheuristics based methods have proven to be the most appropriate methods to address such a problem, especially when considered approaches like linear equations in the flow of network load. Also it provides a methodology for the optimal location of DG based on a genetic algorithm (GA) combined with Artificial Neural Network (ANN).

The objective sought is to minimize losses in the network. The GA is used to determine possible locations to DG units, while ANN is used to calculate active power losses, thus avoiding the use of software to calculate the load flow. Additionally, the GA has a Local Search subroutine (LS) running in each iteration to ensure best generations.. To test the efficiency of these methods, they have been made various tests in a distribution system (34 bars), that is widely used in the technical literature

3.6 Mathematical Formulation

The objective function of the proposed problem is to improve the voltage profile and reduce system losses. To this end the indexes defined in (Chiradeja and Ramakumar 2004) described below were taken. The rate of voltage profile, denoted as IPT, is defined by equation (3.2). This index takes into account not only the voltage, but also the bars thereof as load factor. This makes it more important to maintain proper tension in bars higher demand.

$$IPT = \sum_{i=1}^{N} = V_i \, L_i \tag{3.2}$$

Variables: V_i: Tension in the bar i (p.u); L_i : Load bar i (p.u); and N: Total number of bars. The rate of improvement of voltage profile, denoted as IMPT is given by the equation (3.3).

$$IMPT = \frac{\{IPT_{\{wDG\}} - IPT_{\{woDG\}}\}}{\{IPT_{\{woDG\}}\}} \times 100 \tag{3.3}$$

Variables: $IPT_{\{wDG\}}$ is the index of the system voltage profile with DG (pu) and \$ $IPT_{\{woDG\}}$ is the profile index stress the system without DG (p.u.). Note that the IMPT denotes the percentage of improvement with IPT without DG. The second objective is to reduce active losses for those losses are compared with the system with and without DG, given by the expressions (3.3).

$$IPT_{\{wDG\}} = \sum_{K=1}^{N} I_{\{K,wDG\}}^{2} \, R_K D_k \tag{3.4}$$

Variables:

$IPT_{\{wDG\}}$: Index line losses considering in DG.

R_k: Resistance in line K (p.u / km).

D_k : Length in line K (km).

$I_{\{K,wDG\}}^{2}$: Current line k with DG (p.u).

$LL_{\{woDG\}}$: Index line losses without DG.

$I_{\{K,woDG\}}^{2}$: Online K stream without DG (p.u).

The rate of reduction of losses in the income tax line is given by equation (5):

$$IRPL = \frac{\{IPL_{\{wDG\}} - IPL_{\{woDG\}}\}}{\{IPL_{\{woDG\}}\}} \times 100 \tag{3.5}$$

The objective function is to minimize the reduction rates of losses and improving the voltage profile. In this case you should be using weighting factors W1 and W2 dimensions for each rate in order to assess their importance. The optimization problem to solve is described by equations (3.6) to (3.19).

$$f(x) = w_{1IRPL} + w_{2IMPT} \tag{3.6}$$

Subject to the equation number 7:

$$0 \leq \ w1 \leq 1;\ m = 1, 2 \tag{3.7}$$

$$\sum_{m=1}^{2} w_m = 1 \tag{3.8}$$

$$u_i\ P_{\{Gi\}} - P_{\{Di\}}\ -\ V_i \sum_{k=1}^{nb} \left[V_k \left(g_{\{ik\}} cos\left(\theta_{\{ik\}}\right) + b_{\{ik\}}\ sin\left(\theta_{\{ik\}}\right)\right)\right] = 0 \tag{3.9}$$

$$u_i\ \mathrm{Q}_{\{\mathrm{Gi}\}} -\ \mathrm{Q}_{\{\mathrm{Di}\}} -\ V_i \sum_{k=1}^{nb} \left[V_k \left(g_{\{ik\}} sin\left(\theta_{\{ik\}}\right) + b_{\{ik\}}\ cos\left(\theta_{\{ik\}}\right)\right)\right] = 0 \tag{3.10}$$

$$P_{\{ik\}} = V_{ig_{\{ik\}}}^2 - V_i V_{kg_{\{ik\}}} cos\left(\theta_{\{ik\}}\right) - V_i V_k b_{\{ik\}}\ sin\left(\theta_{\{ik\}}\right) \tag{3.11}$$

$$Q_{\{ik\}} = V_{ib_{\{ik\}}}^2 - V_i V_k b_{\{ik\}} cos\left(\theta_{\{ik\}}\right) - V_i V_k b_{\{ik\}} sin\left(\theta_{\{ik\}}\right) \tag{3.12}$$

$$S_{\{ik\}}^2 = P_{\{ik\}}^2 + Q_{\{ik\}}^2 \tag{3.13}$$

$$P_{\{Gj\}}^{\{min\}} \leq\ V_i \leq\ P_{\{Gj\}}^{\{max\}} \tag{3.14}$$

$$V_i^{\{min\}} \leq\ V_i \leq\ V_i^{\{max\}} \tag{3.15}$$

$$S_{\{ik\}} \leq\ S_{\{ik\}}^{\{max\}} \tag{3. 16}$$

$$N_{\{DG\}} \leq\ N_{\{DG\}}^{\{max\}} \tag{3.17}$$

$$u_i\ \in \{0,1\} \tag{3.18}$$

And as the minimization of losses and is given as the following:

$$Min \sum_{\{r=1\}}^{\{NR\}} I_r^2 R_r \tag{3.19}$$

$P_{\{Gi\}}$ And $Q_{\{Gi\}}$ are the active and reactive power respectively, delivered by a unit of DG if it is located in the bar i. Note that not all bars have DG. DG for each unit must be assigned to a binary variable calledu_i. For simplicity, it is not considered that the DG injects or takes reactive power from the network, $so\, Q_{\{gi\}} = 0.$ $P_{\{DI\}}$ and $Q_{\{DI\}}$ corresponds to power demands active and reactive bar i, respectively. nb is the number of bars, $\theta_{\{ik\}}$ is the angular opening between the bars and k; $g_{\{ik\}}$, and $b_{\{ik\}}$ are the real and imaginary, respectively, of the nodal admittance matrix parts. Constraints (3.9) and (3.10) represent the balance equations and reactive power, respectively. Restrictions (3.11), (3.12) and (3.13) represent the equations of active power flow, reactive and apparent power, respectively. The restrictions (3.14), (3.15) and (3.16), consider the power limits injected by the DG, limits voltage network and load flow limits, respectively.

The Constraint (3.17) indicates the maximum number of units DG to consider and restriction (3.18) indicates the binary nature of the variables u_i 1 if DG and 0 if no DG. The model described by equations (3.6) - (3.19) corresponds to a problem mixed integer nonlinear programming, highly dimensional and non-convex having multiple local optima, which justified its solution using the search methods illustrated in this thesis.

On the other hand in (3.19) Where NR is the number of branches of the network, I_r is the current through the branch r and R_r is the resistance of the branch r. When installing DG network demand is reduced and this can be reflected in a reduction in branch currents and therefore, in system losses. However, over sizing of DG may have the opposite effect. The equality constraints are given by the equations of balance of active and reactive power, represented by equations (3.20) and (3.21) respectively.

$$P_{\{Gi\}} - P_{\{Di\}} - P_i(V, \theta) = 0 \tag{3.20}$$

$$Q_{\{Gi\}} - Q_{\{Di\}} - Q_i(V, \theta) = 0 \tag{3.21}$$

$P_{\{Gi\}}$ and $Q_{\{Gi\}}$ are the active and reactive power, respectively, delivered by a unit of DG if it was located in the bar i. In this case the bars are all DG, so that for each DG unit of a binary variable that takes a value of 1 is assigned if the unit is located on the bar.

Corresponding y=0 otherwise. For simplicity, it is not considered that the DG inject or take reactive power from the network, so $Q_{\{Gi\}} = 0. P_{\{Di\}}$ and $Q_{\{Di\}}$ correspond to the demands of active and reactive power at the bar i, respectively. Finally, $P_i(V,\theta)$and $Q_i(V,\theta)$correspond to net injections of active and reactive power at the bar i, respectively, calculated by the equations (3.22) and (3.23) respectively.

$$P_i V, \theta = V_i \sum_{k=1}^{nb} [V_k \left(g_{ik} cos(\, \theta_{ik}\,) + b_{ik} sin(\theta_{ik})\right] \tag{3.22}$$

$$Q_i V, \theta = V_i \sum_{k=1}^{nb} [V_k \left(g_{ik} isn(\, \theta_{ik}\,) + b_{ik} cos(\theta_{ik})\right] \tag{3.23}$$

Where nb is the number of bars, θ_{ik} is the angular opening between the bars and k; g_{ik}, and $b_{ik}$are the real and imaginary, respectively, of the nodal admittance matrix parts. In the equality constraints they have also included the expressions describing the flow of active and reactive power on the lines, as shown in equations (3.24) and (3.25) respectively:

$$P_{\{ik\}} = V2_{ig_{\{ik\}}} - V_i V_{kg_{\{ik\}}} cos\left(\theta_{\{ik\}}\right) - V_i V_{kb_{\{ik\}}} sin\left(\theta_{\{ik\}}\right) \tag{3.24}$$

$$Q_{\{ik\}} = -V2_{ib_{\{ik\}}} - V_i V_{kb_{\{ik\}}} cos\left(\theta_{\{ik\}}\right) - V_i V_{kg_{\{ik\}}} sin\left(\theta_{\{ik\}}\right) \tag{3.25}$$

Finally, the magnitude of the power apparent can be expressed in terms of active and reactive power as shown in equation (3.26).

$$S_{\{ik\}}^2 = P_{\{ik\}}^2 + Q_{\{ik\}}^2 \tag{3.26}$$

The inequality constraints should consider the power limits injected by DG, limits of voltage on the network and load flow limits as shown in equations (3.27), (3.28) and (3.29) respectively. In this case superscripts min and max indicate the minimum and maximum, respectively.

$$P_{\{Gi\}}^{\{min\}} \leq P_{\{Gi\}} \leq P_{\{Gi\}}^{\{max\}} \tag{3.27}$$

$$V_i^{\{min\}} \leq V_i <= V_i^{\{max\}} \tag{3.28}$$

$$\mid S_{\{ik\}} \mid \leq S_{\{ik\}}^{\{max\}} \tag{3.29}$$

3.7 Methodology Structure

To address the problem of optimal location and sizing of DG described in the previous section four techniques were used combinatorial optimization: Simulated Annealing, Variable Descending Search Environment, Genetic Algorithm and Hybrid Genetic Algorithm. A brief description of the technical solution adopted in this thesis is presented. Also this strategy implemented for optimal location of DG is a hybrid GA involving an ANN and Local Search. The following describes in detail the implemented methodology.

3.8 Heuristic methods

Since the early 1990's, development systems are based on current search techniques that have been developed. These heuristic methods simulate physical spectacles, creature's evolution, and creature's behavior. Many applications of these heuristic techniques to the distribution system optimization have been tried in the last 15 years. An essential idea of heuristic search is that of neighborhood search [3]. In the setting of distribution system problem, agreement assumes that a possible solution is specified by *z*, where the usual of all possible solutions is indicated by *X*, and the rate of solution *x* is indicated by *c(z)*. For each solution *z* has an connected set of neighbors, *N(z)* c *z*, called the neighborhood of *z*. Each solution z ' E *N(z)* can be extended directly from *z* by an action called "move", and *z* is supposed to move to z ' when such an act is performed.

3.8.1 Simulated annealing (SA)

The SA or simulated annealing is based on emulation annealing steel and ceramics, a technique that involves heating and then slowly cooling the material to vary their physical properties. This procedure was introduced in [9]. In each iteration of the SA some neighbors of the current status is evaluated and probabilistically decide between making the transition to a new state or remain in the current state. If the neighbor solution enhances the value of the objective function is accepted with probability 1, otherwise the probability of accepting by the Metropolis criterion given by equation (3.30) where the parameter c corresponds to the temperature.

$$Prob(accept\ \acute{x}) = \begin{cases} 1 & , f(\acute{x}) < f(x) \\ \exp\left(-\dfrac{f(\acute{x}) - f(x)}{c}\right) & , f(\acute{x}) \geq f(x) \end{cases} \tag{3.30}$$

SA assesses unattractive solutions in the early stages, then as the temperature parameter is reduced, the search becomes more selective, lowering of declines in the objective function. The best solution will be accessed by the algorithm that gives the heuristic solution.

3.8.2 Variable Search Environment Descending (VSED)

Environment Variable Search (EVS) is a metaheuristic that changing neighborhood (also known as environment structure) in a local search is based. The EVS has different variations, receiving the name down, reduced, basic or general EVS. In this paper an extension of EVS calls as Variable Search Environment Descending (VSED), in which the current solution obtained from the change in a local search was implemented; as long as this one has found a better solution. The algorithm for VSED illustrated below [4]:

Initialization: Select the set of environments, structures $N_k, k = 1, \ldots, k_{\{max\}}$ to be used in the descent. Find an initial solution x;

Iterations: Repeat until no improvement is obtained, the following sequence: (1) Make$k \leftarrow 1$; and (2) Repeat until $= kmax$, the following: (a) Exploration of the environment: Find the best solution $x'\ of\ the\ k^{\{th\}}$ neighborhood of x(x^\prime \in N_k (x)); and (b) Move or not: If the obtained solution $x^\prime$ is better than x, do $x \leftarrow x'\ k \leftarrow 1$; otherwise do $k \leftarrow k + 1$

In the study presented in this thesis, environments or neighborhoods they were defined as the size (increase or decrease the capacity of the DG) and location (DG move to a neighboring node).

3.8.3 Genetic Algorithm (GA)

Genetic algorithms are part of the evolutionary techniques can be used to solve optimization problems. This method is based on the concept of natural selection and survival of the fittest individual [10]. The general routine of a GA is to generate an initial population of random or pseudo-random. Each individual in the population is defined by a string of bits. In this case, the objective function to evaluate power flow it runs considering the location and sizing of the DG. With the results of flow rates and levels of voltage losses are calculated. For selecting a given tournament number of individuals made. The number of tournaments is equal to the size of the population. Recombination is made in one randomly selected point. The mutation is changing a bit (zero to one) randomly with a probability of occurrence given. Individuals generated in the process of recombination and mutation replace existing individuals if they are better than their predecessors. The maximum number of iterations or the maximum number of iterations without improvement of the objective function, two stopping criteria are considered.

For the coding of the problem we chose a string bit of ones and zeros (chromosome that will be represented as gene in the genes set). The algorithm is coded to locate at most 5 bars generators in the system. In the coding 6 binary numbers used to locate each unit in bars in the DG system. This structure would allow encoding from 0-63; consequently, the numbers do not exist in the system as bars they corrected when evaluating the objective function. Table 3.2 illustrates the coding. In this case it indicates DG at nodes 1, 13, 9, 4 and 2.

Table 3.2: Coding Example

	DG1	DG2	DG3	DG4	DG5
BUS	1	13	9	4	2
BINARY STRING	000001	001101	001001	000100	000010

To run the GA an initial population of n individuals are initially generated randomly, each with a similar to that presented in Table 2.3 For each structure of individuals of the initial population should be evaluated by the adaptation function in this case, the system losses. For this an ANN which will be explained in the next section it is used. From the initial population, and based on its adaptive function, it must select individuals who inherit their characteristics to the next generation. For the selection of these individuals a binary tournament was implemented. For the generation of new individuals recombines with the information from parents. Recombination is used in one randomly selected point in this case, as illustrated in Figure 3.3. After the recombination process, individuals pass local search stage.

Father 1	0	0	1	1	1	0	0	1	1	1	1	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0
Father 2	1	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0

Cutting Point

Child 1	0	0	1	1	1	0	0	1	1	1	1	0	0	0	1	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0
Child 2	1	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0

Figure 3. 3: Recombination example

3.8.4 Hybrid Genetic Algorithm (HGA)

Hybrid methods seek to combine the advantages of two or more metaheuristics for high quality solutions. The most common hybrid methods combine the population methods (Genetic Algorithms, algorithms based on ant colony, algorithms based on bee colony) with local search methods (Simulated Annealing, Variable Search Environment) or exact methods (linear programming, nonlinear) with heuristic methods. This paper presents a method population listed in (GA) combined with a local search method (VSED) was implemented. The flowchart of the implemented algorithm is illustrated in Fig.3.4. HGA structure retains essentially the same GA described in the previous section; however, after mutation and before replacing the individuals of the next generation one is performed in order to find better quality individuals in each generation. As already described in the GA, only included in the new generation, those subjects exhibiting improvement in the objective function.

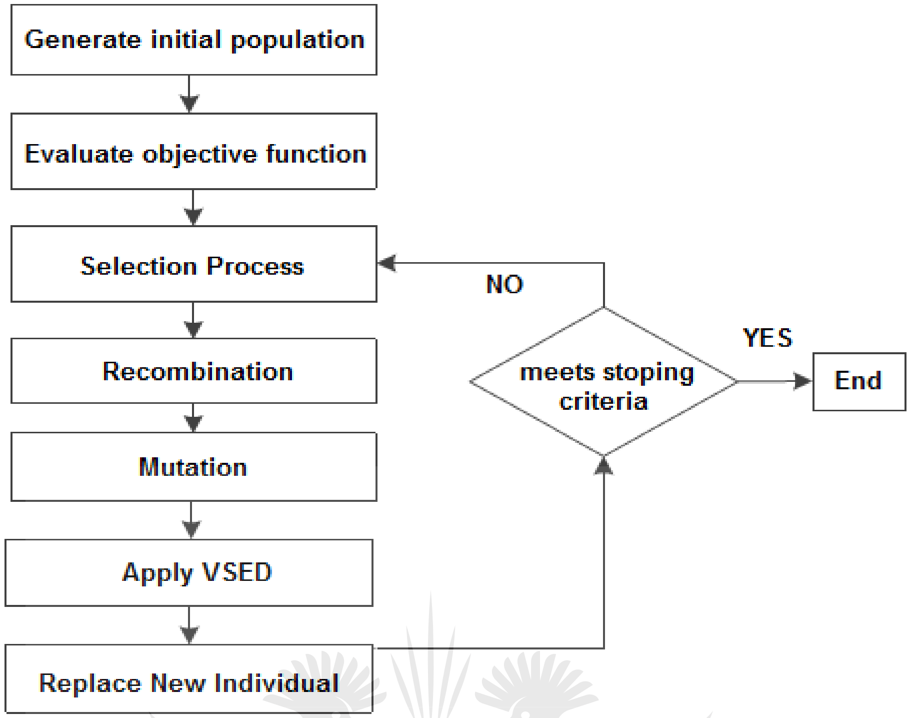

Figure 3. 4: Diagram of HGA Algorithm

3.8.5 Local Search

Local Search evaluates possible solutions within a predefined neighborhood and choose the best solution of the neighborhood. For the selected system, for each iteration of a GA neighborhood it was generated by changing a bit of the solution in each of the positions of the chromosome. The main advantage of the local search is to find solutions of high quality in the first iteration of the algorithm, which favors its convergence. In order to calculate active power losses in the system which this paper aims to locate distributed generation. Hence, ANN is trained, validated and tested. Through the ANN target function that is to minimize system. In this case the neural network allows the system to estimate losses for each of the individuals in the population, avoiding the load flow calculation by conventional methods.

Chapter Four: The Adopted Methods Extracted Results Behavior and Analysis

4.1 Evaluate the Performance

The AG two SD was tested with different topologies: a distribution network with 33 kV of 12.66 bars (33-B system))and a section SD company Pacific Gas and Electric in San Francisco, United States of 12.66 kV to 69 bar (System 69-B). The first network consists of a source, 31 nodes or load bars, sections 31 and feeder lines 5 binding lines. The second test comprises a source 68 load nodes, 68 sections of feeder lines, and lines 5 binding node.

In the network, each line segment is associated with a switch. On each of these optimization method was used to reconfigure the system with minimal Losses,

Maintaining the following conditions:

- The network configuration must be radial to the protections operate properly.
- All sections of the feeders must be energized and their distribution transformers connected.
- There should be overhead in any part of the installation.

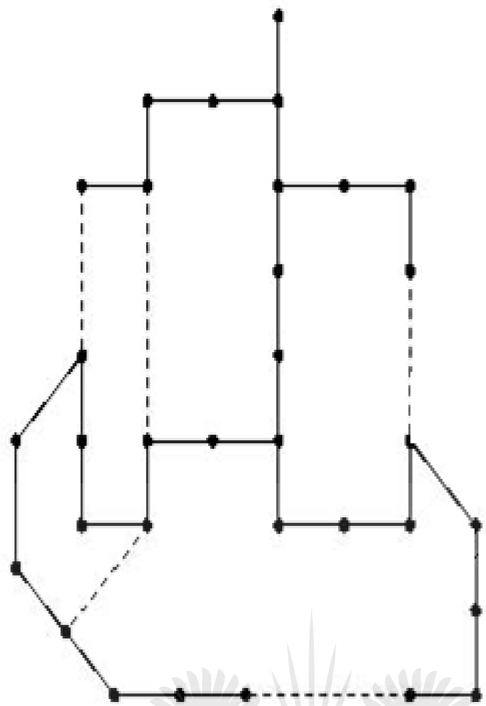

Figure 4. 1: Nodes Network

As a power flow traditional methods for solving power flow study the problem of reconfiguration of applying simplified calculations networks. Such approaches despise terms while not excessively affect the final results regarding calculations employing complete formulas, become important in the case of large networks. Therefore, the computational time involved in applying an accurate method is excessive for use in real time.

From the background studied, different methodologies for the calculation of power flow is analyzed and found that the most appropriate, since they take into account all the powers involved in each line, in the loads and their corresponding power losses. The power flow equations adopted are:

$$P_{i+1} = P_i - r_i \frac{P_i^2 + Q_i^2}{V_i^2} - P_{li+1} \tag{4.1}$$

$$Q_{i+1} = Q_i - r_i \frac{P_i^2 + Q_i^2}{V_i^2} - Q_{li+1} \tag{4.2}$$

$$V_{i+1}^2 = V_i^2 - 2(r_i P_i + x_i Q_i) + (r_i^2 + x_i^2) = Q_i - r_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{4.3}$$

The procedure for the calculation is:

1- Voltage values are set in all nodes only for the first run in 1 pu.
2- The powers of all branches that make up the SD are calculated.
3- Voltage values are updated on all nodes.
4- Returns to Step 2 until the tolerance criterion is reached.

Once you reached the last point SD losses are calculated by adding the power losses that occur in each branch, according to the expression:

$$\sum_{i=0}^{n-1} R_{\{ij+1\}} \frac{(P_i^2 + Q_i^2)}{|\ V_i\ |^2} \tag{4.4}$$

After this process the output deliver the value of fitness (loss) of the individual under evaluation. This value is unique for each configuration, and identifies others, is a measure of how good this setting to optimize the problem.

For modeling and coding Each SD is modeled with conductor sections (branches or lines) and constant power load on the nodes or bars. Each branch in turn is modeled with positive sequence impedance, while charges are the models with active and reactive demands constant. The balanced three-phase system is assumed, so is modeled by phase and power network must be configured radially.

An alternative encoding of SD as offered in Hong trees and HO (2003), with the Prufer number. This method generates solutions that are not feasible to meet as restricting radial nature, so it is necessary to develop an extra algorithm to ensure that each solution provided meets the above restriction. Other shortcomings of this coding is little similarity between the edges of two trees with similar encodings Prufer and the difficulty of adapting the method when the graph of origin is not full. Furthermore, the offspring of these are not necessarily the check, so it is again necessary to apply this extra verification algorithm to the product of crossbreeding and / or mutation offspring. In other words, the extra verification algorithm is applied radiality solutions both "parent" solutions as "daughters" so that the computational time increases proportionally to the number of individuals of each population components or generation.

Implementing this method for SD under study, the extra verification algorithm radiality can be expressed as an equivalent matrix that includes all possible combinations of connectivity between nodes that make up the SD under study. Said matrix is introduced into the evaluation function, which is responsible for returning the loss value corresponding to a particular channel power. This matrix effectively saves the elaboration of this algorithm since when applied once, ensures that any combination of switches to open entering the evaluation function responds to a radial SD. For making the algorithm guidelines provided by Goswami and Basu (1992) and Li et al were followed. (2002).

With respect to the topology of the network and the procedure for defining the meshes are generated in each SD, the most successful methods as regards simplicity, is provided by Ah King et al. (2003). This is the process with some modifications applied in this work. Thus, for the system 33-B arise 5 open switches. If these switches are closed loops or meshes 5, each composed of branches that are numbered starting from the origin or source node are formed. The node receiving the current flow indicates the number of the branch, so that it is always contemplated that the original configuration is an option. Mesh thus defined considers the initiation of a switch and only one mesh.

Thus it is formed a chain where each element represents a position in the expression of the corresponding mesh, which indicates the number of the switch to open. Thus, any combination that yields responds to a radial configuration.

CHAIN: {[Mesh 1] [Mesh 2] [Mesh 3] [Mesh 4] [Mesh 5]}

For example, if the GA indicates the result of the chain {3 5 1 2 4} means that the mesh opening switch 1 is one that identification is in position 3; the mesh 2 is that switch whose identification is in position number 5; and so on.

The mesh thus defined is its length (the number of branches that make up) is not the same for each. This length determines the upper limit of each variable (gene) is input data for use of GA (the lower limit is 0).

From chain yielding the algorithm, the switches are determined to open and subjected to calculation of power flow. The goal then is to obtain a configuration such that the reduced value of losses is between 6% and 15%, relative to the initial configuration. Optimal parameters simulation Defined parameters inherent topology and coding variables (chain length, upper and lower limits of each variable and power flow), proceed to determine own GA: population, number of generations, variable type input types and ranges of selection, crossover and mutation. For the purpose of finding those who give the best performance of the algorithm development, the behavior of these parameters was analyzed.

For the right choice of selection method (Roulette, Tournament, Stochastic Uniform, Uniform, Remaider) Several runs were made for each option and the time taken to reach the optimum. The results are shown in table3 . Analysis it appears that the uniform selection is discarded for having a 10% chance of finding the optimal solution of total runs performed.

It was found that the choice of the selection method does not affect too much on the total calculation time as they differ on average from each other in a negligible value. Therefore, for 33-B system selection for the tournament it was used because the variables are scarce and therefore the search space is reduced. In addition the time obtained can be further reduced by changing the number of individuals participating in the tournament.

For the most appropriate choice of mating, several runs (performed table4.1), being both spread type, a point and two cutting points present in times better performance, but show greater efficiency facing each other . For this work we chose to use a cross at two points, as in the case of not finding the nearest optimal solution to it you'll find at 10.625 sec. compared to 20.015 sec. disseminated type. As for the fraction of crossover, we started from individuals not reproduced to generate new populations (0% of the population) to new sets generated with the entire board (100% of the population). That is from 0 to 1, steps of 0.05

Table 4.1: Time to reach the optimum [sec.]. Type Selection (indicated with an asterisk values * "belong to different optimal configurations

	Types Selection				
No.	Roulette	Tournament	Stochastic uniform	Remainder	Uniform
1	10,407	13,156	9,797	18,078	* 14,078
2	11,078	8,172	16,516	11,047	10,703
3	16,422	10,016	* 7,547	19172	* 8,406
4	17,469	10,922	9,938	15,328	* 10,765
5	11,484	8,312	10,344	16156	* 11,891
6	8,031	7,813	16,469	12,954	* 13,984

7	11,437	14,546	8,375	10,234	* 12,765
8	9,187	* 10,625	13,797	10,687	* 11,875
9	14,735	11,406	10,969	9,531	* 19,515
10	12,281	8,719	11,156	12,235	* 12,656
Average [sec.]	12,253	* 10,625 10,340	7,547 11,929 *	13,542	* 12,881 10,703

Table 4.2: Time to reach the optimum [sec.]. Crossover Type (The values indicated with an asterisk "*" belong to different optimal configurations)

Crossover types

No.	Disseminated	A point	Two points	Intermediary	heuristics
1	* 20,015	8,672	13,156	9,302	* 9,891
2	9,672	* 11,422	8,172	* 9,176	9,609
3	9,406	* 7,906	10,016	12,156	18,340
4	15719	8,188	10,922	10,671	12,336
5	8,547	9,422	8,312	* 9,141	13,708
6	11,078	14,532	7,813	* 9,883	15,746
7	14,281	8,578	14,546	* 9,401	10,151
8	9,109	9,500	* 10,625	* 10,226	11,352
9	9,969	9,531	11,406	12,259	10,433
10	9,422	7,812	8,719	* 8,346	* 10,123
Average	* 20,015 10,800	9,529 *	* 10,625 10,340	11,097	12,709

[Sec.]	9,664	* 9,362	* 10,007

The results are dumped, which are represented three loss values: a) for the optimal solution is 134.7321 kW; b) the following value losses for setting opening closer to the optimal solution, which is 134.9930 kW switches; c) the value of a configuration that is not near the optimum and possibly a local optimum, 137.5293 kW. The ordinate represents the number of times it is achieved that value losses in 5 runs and the abscissa represent the fraction of crossbreeding.

From the graph it can be deduced that for fractions less than 0.7 is crossing (for five runs) always optimal, and above 0.9 values, the number of times that the optimal solution is reached decays to the once they appear close to optimal solutions. It is clear that to a fraction of less than or equal to 0.7 crossbreeding computing time involved for such a solution is very important, while for values greater than 0.7, the time it takes to obtain an optimal solution GA, or very close to the optimum, it is significantly lower. Moreover, for the fraction of crossover value equal to 1, the solution is found very quickly, but none of the runs the optimal solution is reached. It can also be noted that the values determined by the range between 0.8 and 0.95, the optimal solution search time is acceptable.

This analysis concludes that there must be a compromise in the choice of the appropriate fraction crossing both to obtain a very good solution to reduce the computational time to an acceptable value. Therefore, the range found [0.7; 0.9] to the taken to the operation of the GA, a value of crosstalk fraction equal to 0.85 was taken.

Also it is taken into account the type of Seedling (crossover), where again several runs varying type (spread, one point, two points, intermediate, Heuristic) were performed. The time employed was determined to achieve optimal (table 4.2).

The analysis shows that the best performance of the show times the spread type, one point and two point. Of the three, there is a method that stands out above the other with respect to saving computation time, even though the method for point is that, on average, has more advantage, and shows a 90% probability find the best results. Both options (spread and colon) bring saddled the same results, but for the purposes of this paper type two points will be used, as in the case of not being the, the closest to this optimal solution it will be in half time (10.625 sec.) if the spread is chosen method (20.015 sec.).

As for the type and range Mutation available options are two: Uniform and Gaussian. In this case, the choice fell on the uniform, since the Gaussian mutation rate decreases as they move generations, so that some regions of the search space cease to be explored, eliminating potential solutions to solve the problem. On the other hand, the Uniform constant mutation. With respect to the mutation rate is noteworthy that this should be high enough to promote a sufficient amount of diversity in the population without destroying individuals.

The configuration obtained in the first run of the algorithm indicated the following switches open: 7, 9, 14, 32 and 37 Fig3.6, being the optimum. Therefore, there is no other configuration that can decrease the value of the power loss below 134.7321 kW.

Furthermore, stress profiles were analyzed and found to be the lowest value was 0.9424 pu (31 bar), which implies a voltage drop across the bar 6%, which is less than the maximum value allowed by national law: 8% in medium voltage. In other countries, this value decreases to 5%. A new run was made taking into account this restriction, finding that there is no configuration having a bar with a drop level less than or equal to this voltage value. The configuration that approaches the performance of this restriction corresponds to the opening of the switches 7, 9, 14, 28 and 32 with a value of 134.9930 kW losses since the bar with less tension accuses a voltage drop 5.76% (31 bar).

Similarly, the same analysis for the system bus 34 was performed, yielding the result shown in table 4.3. In this case, the network topology determined by the opening of switches 58-61-72-14-74, satisfies the condition of optimal configuration and also with the voltage drop (-ΔV) maximum 5% and 8% imposed as restrictions. The hypothesis of reduction of losses has been satisfied favorably as 51.3% reached exceeds the range of 6% to 15% proposed aim.

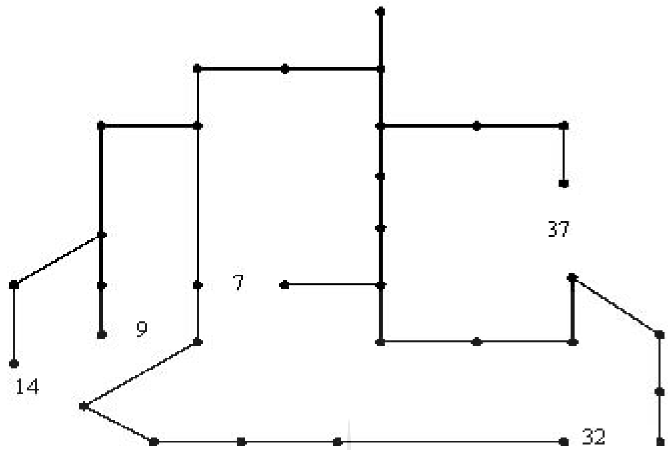

Figure 4. 2:Network with open Nodes

Table 4.3: Resultant Configuration for 34-Bus

configurations		Loss [kW]	Reduction losses%
Initial	70-71-72-73-74	188.2002	
optimal	58-61-72-14-74	91.6489	51.3
Restriction -ΔV = 8%	58-61-72-14-74	91.6489	51.3
Restriction -ΔV = 5%	58-61-72-14-74	91.6489	51.3

Another nodes structure in order to validate the proposed methodology is a 34 bar system illustrated in Figure 4.3. This system is similar in topology to IEEE system 34 bar, but a single-phase version. The load distribution on the nodes shown in Figure 4.4. It can be seen that much of the demand is located far from the substation. For simplicity we assume that all nodes are eligible for DG, but the number of units in DG has been limited to 5. For the problem under study was defined as a maximum number restriction of DG units by bar with a capacity of 1 MW. Table 6 presented the summarizes of the parameters used in the GA.

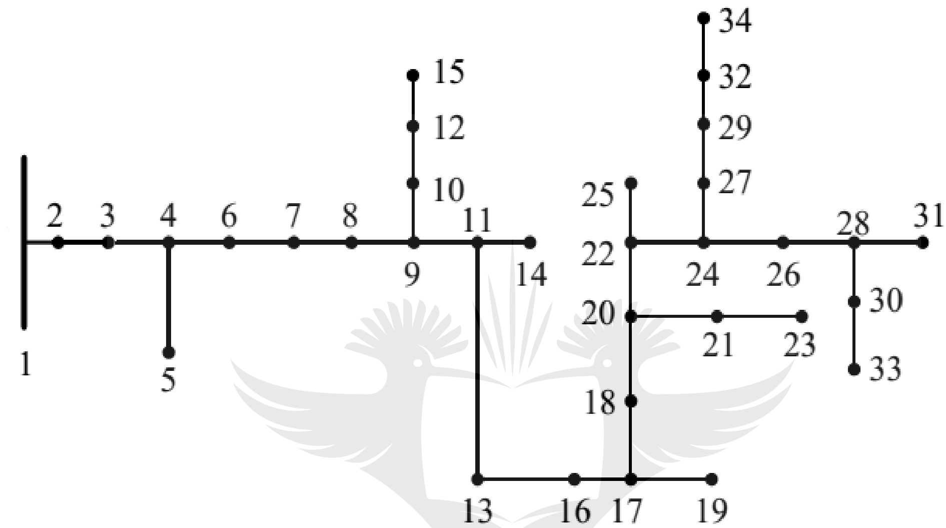

Figure 4. 3: 34 bar testing system

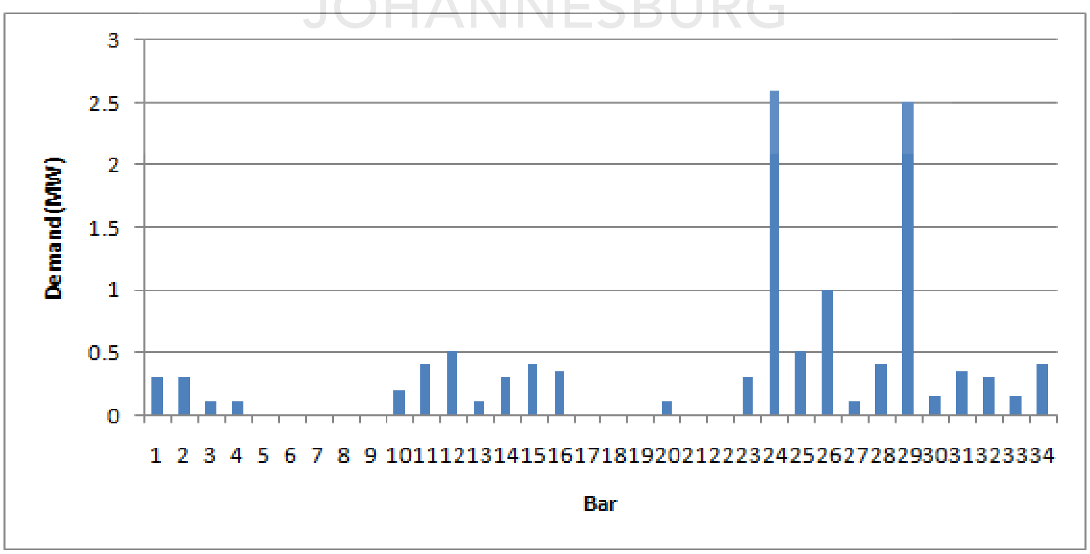

Figure 4. 4: Distribution of demand in the tested network

Table 4.4: GA parameters

Parameter	Value
Population Size	20
Max generation	40
Number of Cutting Points	1
Crossover Probability	0.95

To assess the loss a neural network feedforward that structured by two layers with a layer of hidden sigmoid function and an output layer with a linear function. The hidden layer consists of 20 neurons and the output layer with just one neuron. The network was trained with the Backpropagation strategy, a Learning probability of 0.01.

To train ANN consolidates a database of 2280 cases. It was found that once trained, the ANN delivery lost values with similar amount to those obtained with conventional flow program load [10] network. To control infeasible solutions, ANN solutions penalizes high losses looking to discard the GA naturally to the individual, preventing appears on subsequent iterations. Fig 4.5 shows a sample database template used to train the ANN . 70% of the samples were selected for use it in training, 15% for validation and the rest for the ANN test. This allows the network do not just memorize the proposed values, but also to sense and deliver securities under the inference of intermediate values. Training results with the selected network shown, in Table 4.5. Mean square error (MSE) is the difference average of the square in the results and the objectives of the ANN, lower values are better and a zero means no error. The R (Regression R) is the correlation between the results and objectives. A value of R = 1 indicates a close relationship, the relationship 0 means random.

GENE 1						GENE 2						GENE 3						GENE 4						GENE 5					
0	0	1	1	1	0	0	1	1	1	0	1	0	0	1	0	1	0	1	1	0	0	1	0	1	0	0	1	1	0
0	0	1	1	0	0	1	0	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
1	0	1	1	1	1	0	1	0	0	1	1	0	0	1	1	1	0	0	0	1	1	0	0	1	0	0	1	1	0
0	1	1	0	1	0	0	1	0	1	0	0	1	1	1	0	0	1	0	0	1	0	0	1	0	1	0	0	0	1
0	0	0	1	0	0	0	1	1	1	0	0	0	1	0	1	0	0	1	0	1	1	1	0	1	0	1	0	0	0

Figure 4. 5: Sample template for evaluation of cases

Table 4.5: objective function

	Samples	MSE	R
Training	1596	2.32981E-05	9.90097E-01
Validation	342	2.62768E-05	9.90233E-01
Proof	342	1.98193E-05	9.92804E-01

Once the ANN train to calculate the objective function, tests were performed to compare the results, calculating the losses through a conventional power flow. Table 4.6 summarizes the computation times for each evaluation is presented. For this simulation used a Computer Intel Core i3, 2.53 GHz with 4 GB of RAM. In this case FO corresponds to the objective function using a conventional load flow and FO-ANN corresponds to the objective function calculated using ANN.

Table 4.6: GA computation time and system

losses

	Time(s)	Losses (KW)	Decrease %
FO	1.381,92	656,25	20,68
FO-ANN	3.26,51	666,86	19,5

It can be seen that the ANN provides a fairly good solution to the real solution, with a deviation of 1.18%; with the additional advantage that once trained, you can be estimated system losses in less time than conventional load flow. In this system the losses for the base case without DG amounted to 827.41 kW. By incorporating DG losses decreased by approximately 20% (see Table 4.6). The best solution obtained with the GA is illustrated in Figure 4.6. In Figure 4.7 the voltage profile illustrated network with and without DG. It can be seen that the DG and contribute to reducing losses, substantially improves the voltage profile in the network.

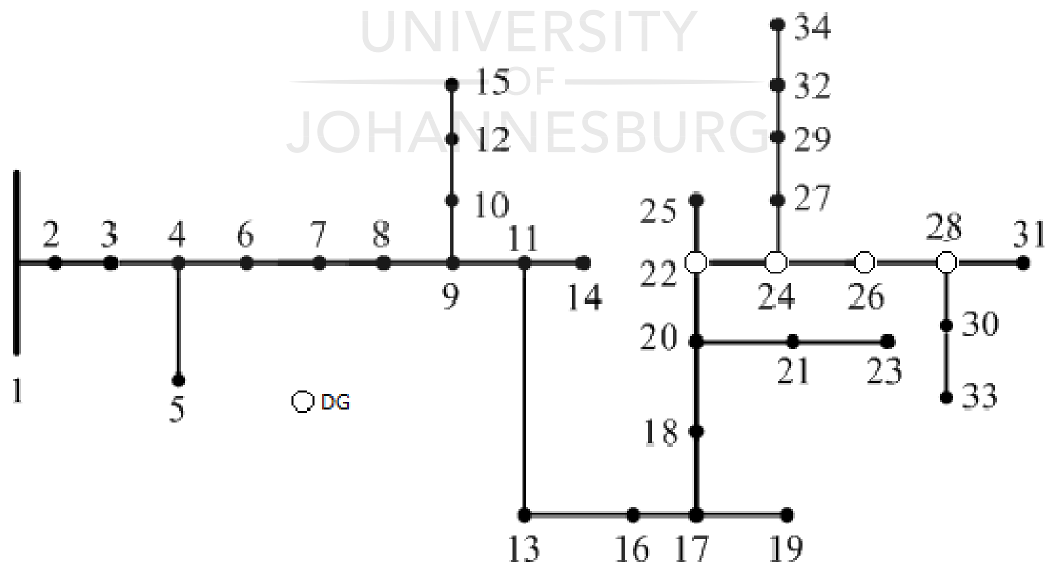

Figure 4. 6: Best configuration found with the proposed methodology

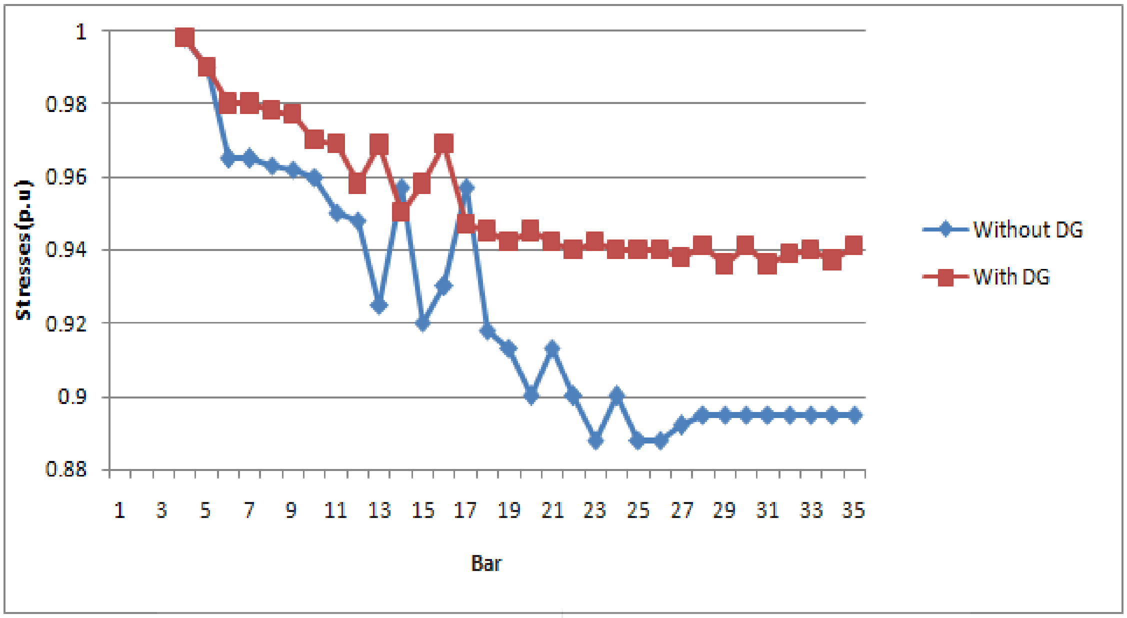

Figure 4. 7: Stresses profile with and without DG.

Another distribution for the demands represented in Fig 4.8 in the aim to measure the algorithms stability.

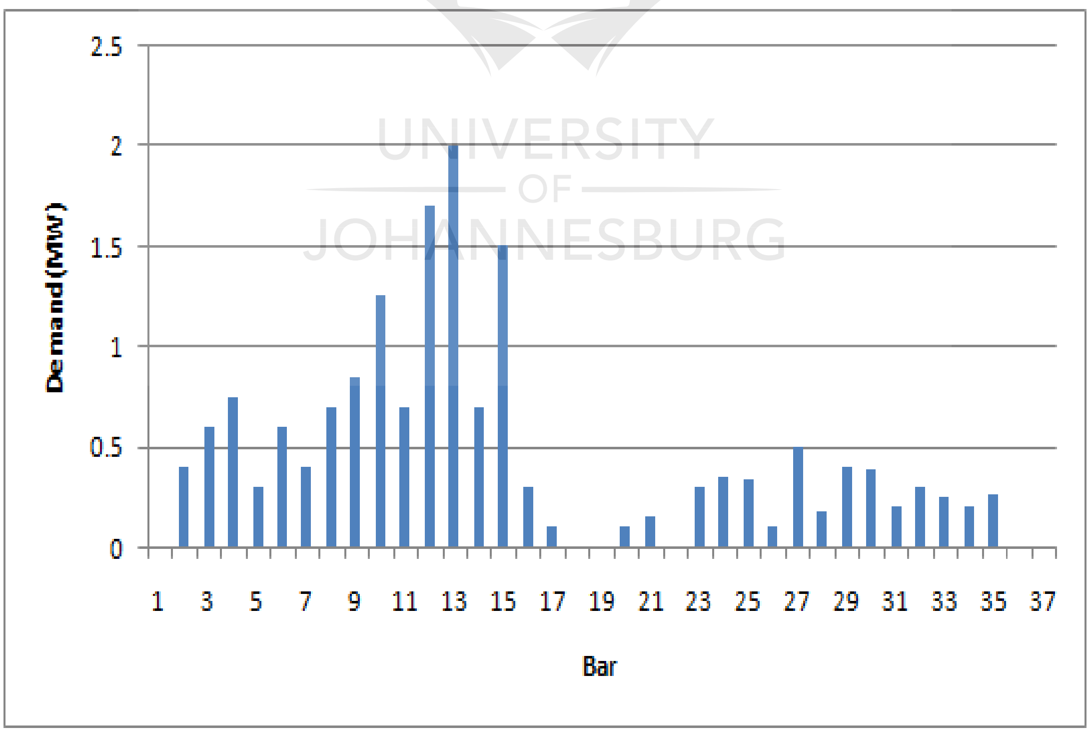

Figure 4. 8: 2nd Demand Distribution

With another test as the following information with encoding a chain of 4 binary bits representing each used generator. The first bit symbolizes the formal of the generator (there generator 1, the generator does not exist 0); the remaining 4 bits represent the power level of the generator. For example, 1000 means a string generator minimum capacity (0.25 MW), while the chain 1111 represents a generator with maximum capacity (2.0 MW).. Table 4.7 illustrated encoding solution candidates. Equal to 4 nb, where nb is the number of binary string bar system is used. According to the adopted coding candidate solution shown in Table 4.8 no DG in the bars 1, 2, 4 and nb-1; while the bar has nb 3 and generators with a capacity of 1.0 and 2.0 MW, respectively.

Table 4.7: Codification of DG size

Code	Size(MW)	Code	Size(MW)
1000	**0.25**	**1100**	**1.25**
1001	**0.50**	**1101**	**1.50**
1010	**0.75**	**1110**	**1.75**

1011	**1.00**	**1111**	**2.00**

Table 4.8: Solution candidates encoding

Bus1	Bus2	Bus3	Bus4	….	Bus nb-1	Bus nb
0100	**0011**	**1011**	**0111**	**……**	**0011**	**1111**

Before starting the optimization process must assign weighting factors to the two objectives under study (IRPL and IMPT) in order to give greater or lesser importance in the search for solutions. This requires a diagnosis without DG base case. This diagnosis is made by a load flow calculation with and without DG. The load flow is performed by software Mathpower [15] DG modeling as bars where you can inject active power. In Fig. 4.9 and Fig. 4.10, the voltage profile and line losses, respectively, with and without DG illustrated.

To illustrate the case with 4 units of DG, each 1 MW located in the bars 5, 10, 15 and 20. In Fig. 4.11 are assumed to be noted that even adjusting the tension in the substation at 1.1 pu, when DG are not tensions the last bars are below 0.9 pu featuring voltage regulation (percentage difference between the maximum and minimum system voltages) exceeds 20%. However, when DG is introduced to the system stresses increase, especially in remote substation bus bar, causing the voltage regulation in these rods is 17.5%.

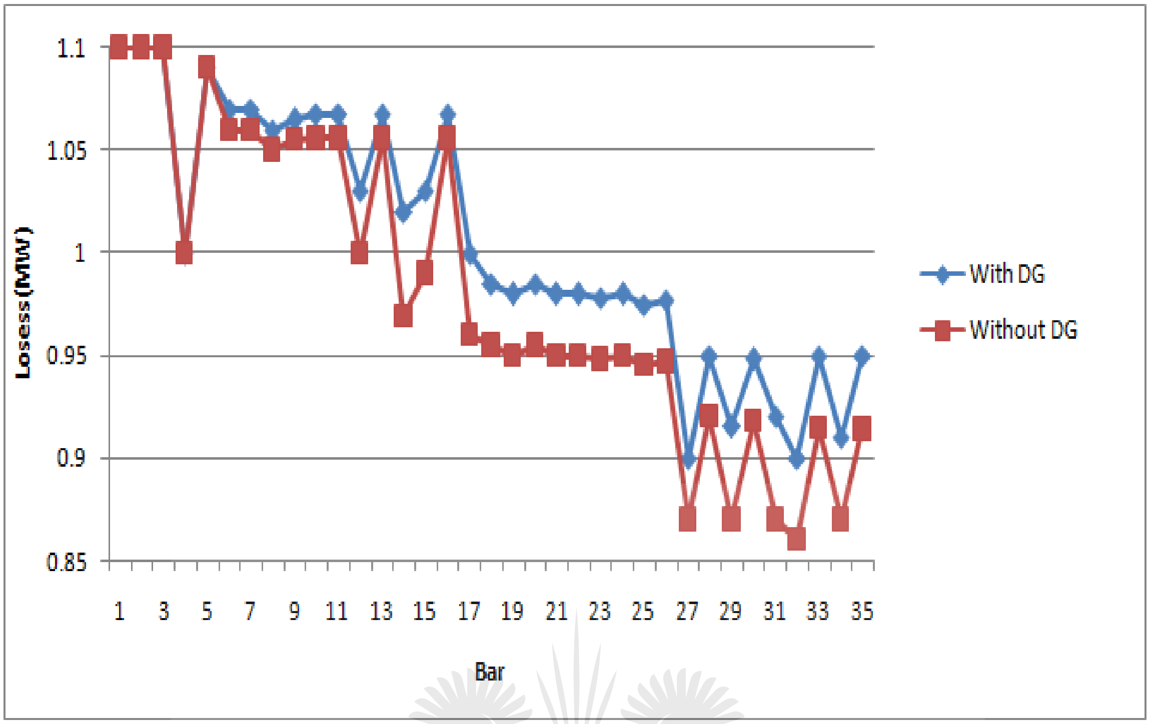

Figure 4. 9: Voltage profile system of 34 bars without DG

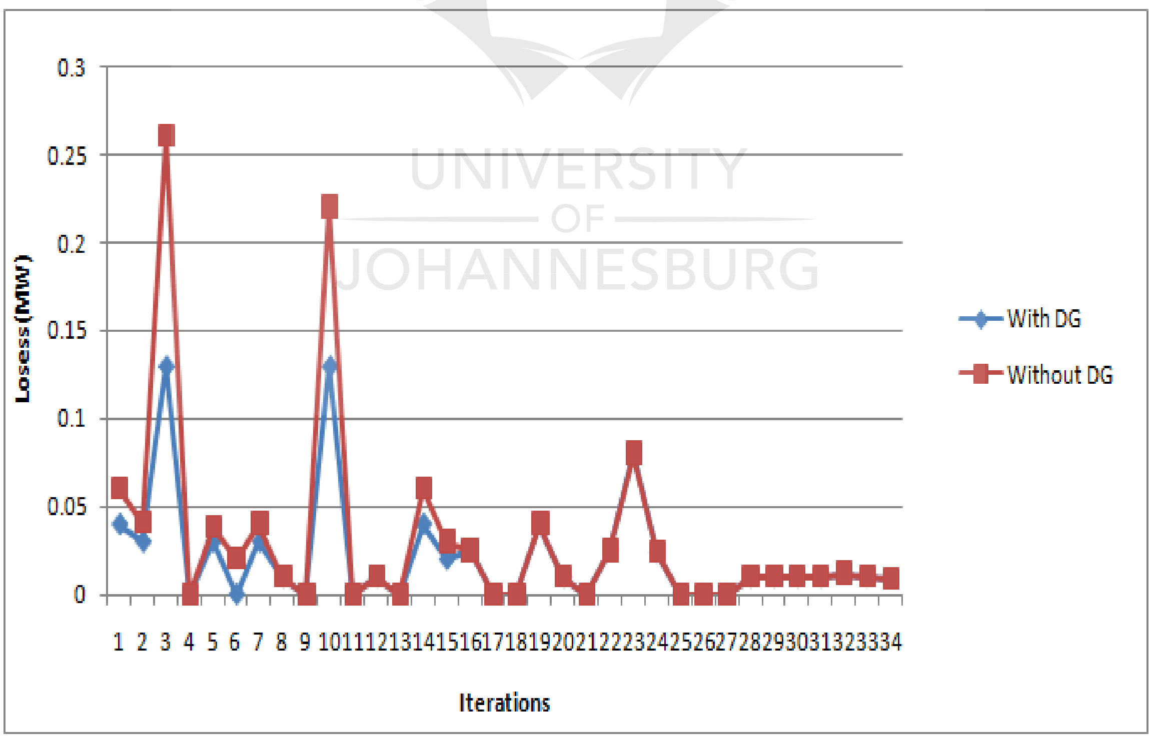

Figure 4. 10: Line losses of 34 bar system with and without DG

On the other hand, total losses without DG amounted to 959.5 kW systems and DG are 555.8 kW. When calculating indices Income tax and IP by the expressions (2) and (5) respectively is obtained IRPL = 41.8848 and IMPT = 1.5135.

These indices are calculated for different solution candidates (location and DG sizing) randomly generated resulting in the data given in Table 4.9. It can be seen that IRPL is much higher than IMPT in all simulations. This is because the percentage of loss reduction is more significant than the improvement in voltage profile. On average, IRPL is about 20 times greater than IMPT as seen in the fourth column of Table 11. If the indexes are optimized without using weighting factors that favor solutions would have to reducing losses on improving tensions. In this case, weighting factors w1 = 0.05 and w2 = 0.95 in order to match the orders of magnitude of the indices IMPT and IRPL give similar importance to both objectives in the optimization process are selected. However, the manager of the planning system can select other values to give more importance to a particular target.

Table 4.9: Values of IRPL and IMPT for candidates with randomly generated solutions

Simulation Trial	IRPL	IMPT	IRPL/IMPT
1	41,884	1,513	27,682
2	50,127	2,806	17,864
3	43,297	2,124	20,385
4	57,487	2,478	23,199
5	34,329	1,878	18,280

6	30,287	1,079	26,070
7	44,238	2,567	17,233
8	30,234	1,969	15,355

To start the SA a base solution that meets the criterion of maximum number of generators is generated. From this solution neighboring solutions that will be accepted according to the criteria stated in equation 19 are explored. This means that as early in the process worsening of the objective function is possible, but as the process evolves the probability of accepting worse quality solutions is restricted. Thus, the principle of seeking diversity is privileged and at the end of it intensifies the search for better solutions. After performing several runs SA algorithm parameters, initial and final temperature was calibrated in 3.0 and 0.5, respectively, and at each iteration the temperature is reduced by 0.01. In Tab 4.10 the best solution found (after 190 iterations) shown in Fig.4.11 and the convergence of the algorithm illustrated SA. In this case the time calculation was 1.2 minutes.

Table 4.10: Best result using SA

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
12	1,7	4,0573	3,9201	7,9774
13	2,0			
22	1,0			
30	1,25			

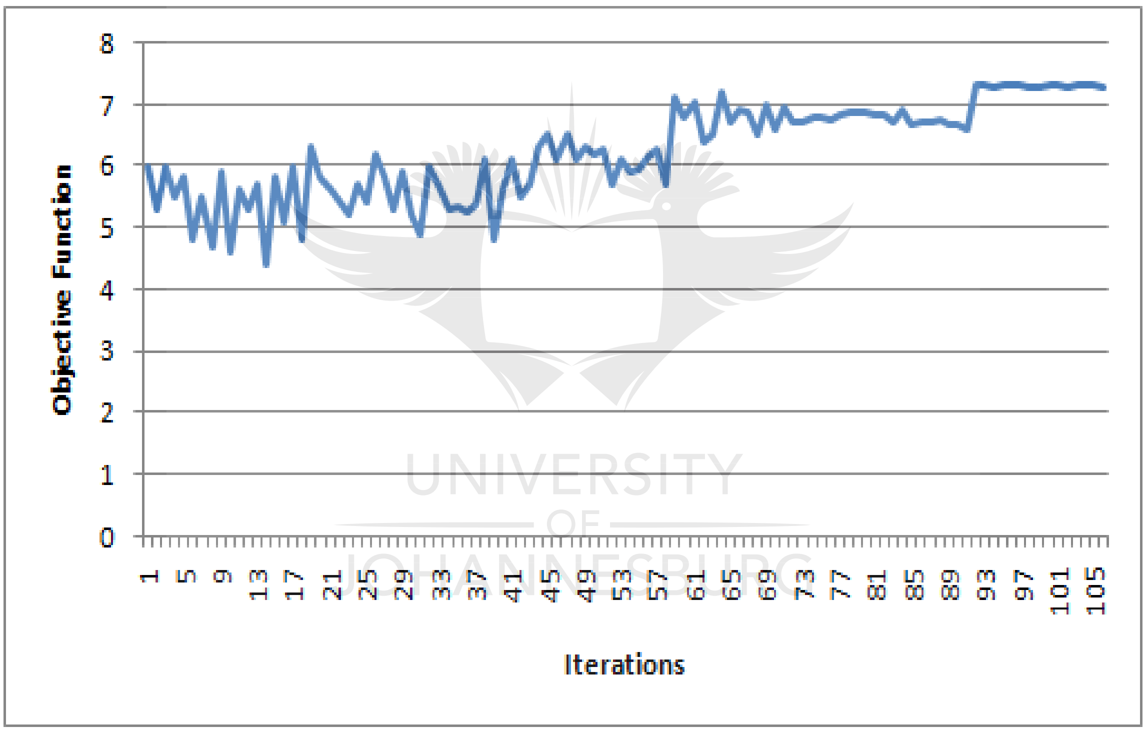

Figure 4. 11: Convergence process in SA

While the results using VSED to make the environment VSED structures we defined: the size and location of DG. Given a base solution structures of individuals seeking to better environment, where explored by following the instructions as described in the Methodology section. The search continues until it passes a certain number of iterations or until no improvement is meets a number of iterations previously established. In Table

V, the best found with VSED illustrated. Here 22 iterations were performed by evaluating structure 8 environment, individuals with a computation time of 2.1 minutes.

Table 4. 11: Best result using VSED

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
5	2,0	3,9274	3,8313	7,7857
10	2,0			
21	1,5			
31	1,5			

Another results for GA is extracted for this experiment as this solution used as coding chromosome structure illustrated in Table 4.11. Initially an initial population of possible solutions are generated from which are new solutions of better quality by implementing selection, recombination and mutation described in the methodology section. To calibrate the parameters of the various tests were performed GA is modifying the initial population size and mutation rates and recombination.

It was noted that few individual initial populations of poor quality responses were obtained. By increasing the number of individuals in the initial population quality improvement solutions, but the computing time increases. The best solution was found with a population of 100 individuals and mutation and recombination rates of 10\% each. The computation time to find the best solution was 2.9 minutes after 90 iterations. In Table 4.14, the best result is shown. In Fig. 4.12, the process of convergence of GA illustrated for different tests. It can be seen that even though the initial populations are of different quality, the GA solutions are similar quality.

Table 4. 12: Best result using GA

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
10	2,5	3,8887	3,7836	7,6723
15	1,5			
26	1,5			
29	1,25			

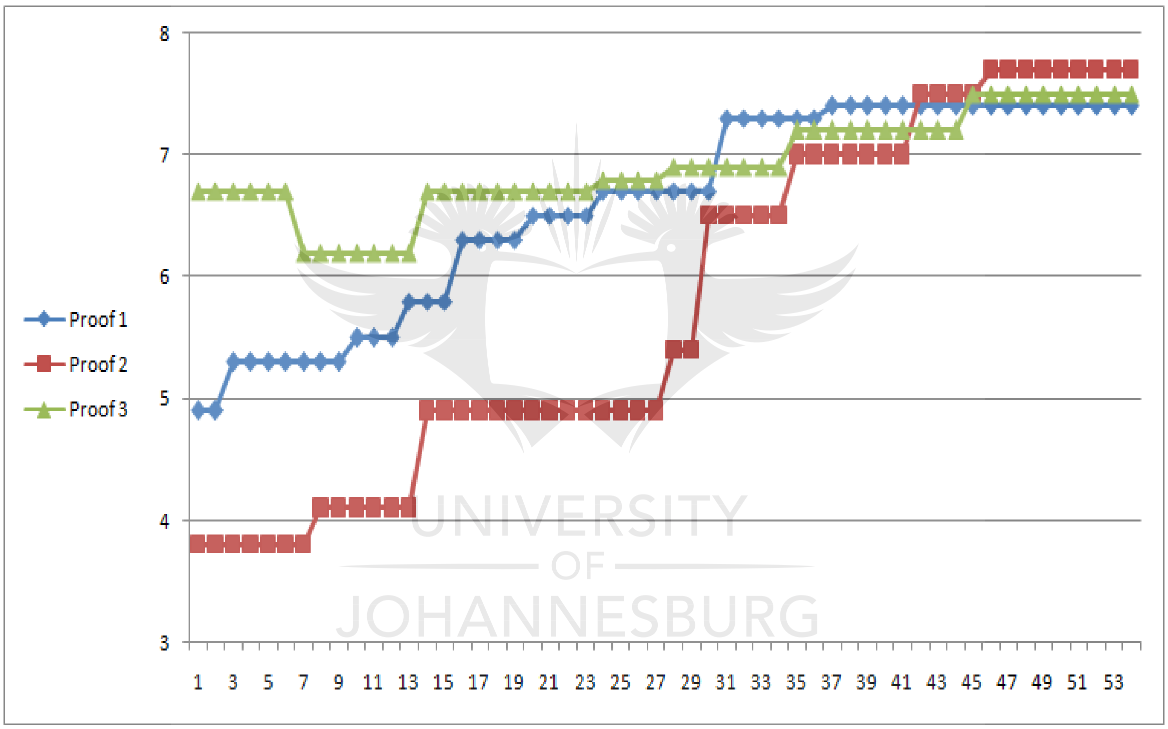

Figure 4. 12: Process of convergence for 3 different GA tests

As mentioned above the HGA implemented combines GA described in the previous section with VSED. In this case, after applying the traditional operators GA and prior to the population replacement is performed to increase the quality of VSED individuals in each iteration. HGA for the same parameters that were calibrated with traditional GA were used. In Table VII the best solution found is presented. It was observed for all tests that the computational time is considerably greater than that required by the other algorithms implemented; however, the quality of response is better. The best answer is found after only 6 iterations a computation time of 12.6 minutes.

Table 4. 13: Best result using HGA

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
12	1,7	4,0573	3,9201	7,9774
13	2,0			
22	1,0			
30	1,25			

4.2 Results Comparison

It was observed that the best result was obtained by the HGA; however, this is the method that it takes longer time to find a high quality solution. Furthermore, the faster the algorithm in converges was the Simulated Annealing. Although, this methodology is faster, the solutions obtained with the other methodologies were of better quality. The VSED require fewer iterations to converge more than SA, but the computing time per iteration is greater, and to be evaluated by iteration, two structures of the neighborhood. Regarding GA it was found that the HGA is to find high quality solutions must be used (100 individuals) large initial populations. In Fig. 4.13 compares the computation time for each of the methods used, where the HGA stands. The best solution found (see table 3.13) it was observed a reduction in losses of 80.2% compared to the base case without DG.

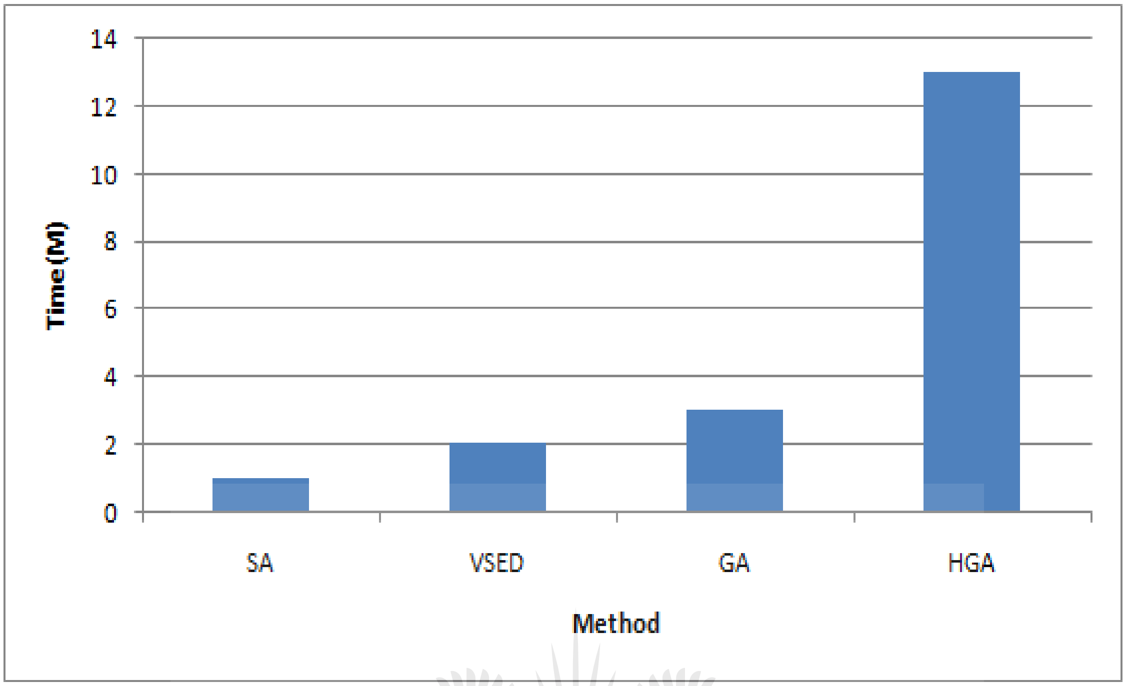

Figure 4. 13: Search time comparison.

Chapter Five: Conclusions and Future Works

5.1 Conclusions

This chapter summarizes the most relevant results achieved in this Doctoral thesis, indicating the contributions made in the design and planning of distribution networks. The advantage of the hybrid algorithms lies in the fact that they are able to offer a potential increase in performance compared to multistart methodsthrough identifying and exploiting global features the user is not aware of beforehand, but if such features are not available, they still offer superior performance to pure EA methods through the more efficient local search.

In addition, it indicates the future research work to be carried out, in which will take as a starting point those that have been expressed in this document.

The following are the results and contributions of this Doctoral Thesis:

- The optimal design of electric power distribution systems through the application of optimization Algorithms. For this purpose two objectives have been considered: Overall economic costs of the distribution and reliability system, subject to the technical restrictions. The location and size have been occupied into the optimization of lines and substations, as well as technical aspects related to the calculation of stresses.

- For the optimal design of the distribution systems has studied with the Influence of the parameters of the number of solutions that forms the external population in the optimal design solutions obtained in the optimization process.

- Multiple numbers of optimization techniques have been applied in order to reach optimum design in distribution systems (HGA, GA, VSED, LS, ANN).

- The results has been shown that the using of optimization methods enhance the behavior of designing DG.

In this thesis, various algorithms were compared to obtain the optimum location and sizing of DG in distribution systems: SA, VSED, GA and HGA. The implemented methodologies based on these optimization algorithms were all successful in finding high quality solutions. In the trialled application tests the best results were obtained using HGA, which combines genetic algorithm and VSED. It was observed that the optimum percentage of DG penetration of the test system varied between 6 and 7 MW installed at the start bar and the end bar for substantial improvement using DG units of 1-2 MW. In addition, the optimum location and sizing for DG allowed a substantial improvement of the voltage profile of the network and reduced losses of 80.2 per cent in the test system. Regarding computation times, the fastest method was SA; however VSED and the HGA showed better results.

Therefore, in this research, it was developed a planning method based on evolutionary algorithms that is able to resolve single-objective and multi-objective distribution system expansion planning problems.

5.2 Future works

The future research works that are proposed to develop are:

- Apply new techniques of evolutionary computation, such as strategies which are being considered for future investigation due to the good results that have been obtained in by applying it in various fields of industrial design.

- Consider the optimal design of integrated electrical networks, i.e. including several voltage levels, primary networks and secondary networks, this being an extremely complex problem which needs to be tackled by modifying the developed tools.

- The application of a Coefficient-evolutionary algorithm. These Coefficient-evolutionary algorithms allow us to concentrate the search for solutions in sub-regions and use a sub-population in each of them, allowing that the method of finding solutions is more efficient from a point of view Computational view.
- Distributed generation. Historically, growth in electric load demand has been served by adding new large central station generating units, building transmission lines and extending traditional distribution systems. An alternative approach under consideration by utilities is to satisfy demand by investing in distributed generation (DO). DO can relieve capacity constraints on the generation, transmission and distribution systems and obviate the need to build new facilities. One way to evaluate a DO option is by determining the reduction in variable costs in the system and the value of deferring capacity investments. The application of multi-objective evolutionary algorithms in this case could prove to be fruitful.

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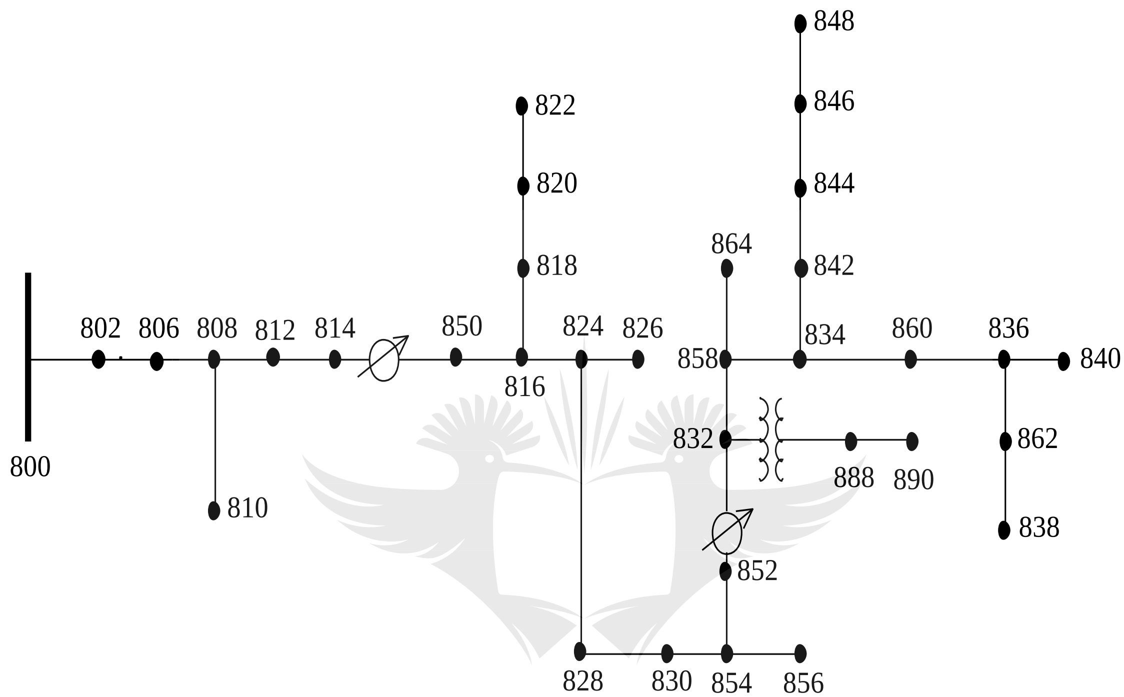
Appendix

Distribution System Analysis Subcommittee



IEEE 34 Node Test Feeder

Type of the Paper (Article)

Electric Power Grids Distribution Generation System For Optimal Location and Sizing – A Case Study Investigation by Various Optimization Algorithms

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Abstract: In this paper a variable's involved in assessing the quality of a distributed generation system are reviewed, aiming to minimize the electric power losses (unused power consumption) and optimize the voltage profile. To provide this assessment, several experiments have been made to the IEEE 34-bus test case and various actual test cases with the respect of multiple Distrubution Generation DG units. The possibility and effectiveness of the proposed algorithm for optimal placement and sizing of DG in distribution systems have been verified. Finally, four algorithms were trailed: simulated annealing (SA), hybrid genetic algorithm (HGA), genetic algorithm (GA) and variable neighbourhood search. The HGA algorithm was found to produce the best solution at a cost of longer processing time.

Keywords: Optimization, Simulated Annealing, Genetic Algorithm, Power Losses, Power Consumption

1. Introduction

In the past decade increased distributed generation (DG) has led to profound changes in electricity distribution networks. Several factors have driven DG (defined as production of electricity close to consumption centers) including new technological advances in the production of electricity on a small scale, a preference for the use of renewable resources, difficulties in network expansion and a growing interest in incorporating demand and active agents in the electricity markets [8]. DG can contribute to reducing losses, improving voltage profile, improving reliability and postponing investments [7]. However, as noted in [5], harnessing the benefits of DG depends largely on its location, sizing and network features. That is why in the past decade's alternative methodologies for proper location and sizing have been explored.

In [6] a literature review of techniques used for the location and optimal sizing of DG in distribution networks is presented. The authors classify the techniques according to analytical methods, metaheuristics and mathematical programming. It should be noted that for the problem under study metaheuristics techniques have significant advantages over classical mathematical programming because of the nonlinear and non-convex relationships in the location and sizing of DG. On the other hand, the main weakness of metaheuristics is that they do not guarantee obtaining a global optimum. However, metaheuristics may provide a solution or set of high quality solutions. Another advantage that lies with metaheuristics techniques is that they allow the use of more detailed models of network operation than the analytical model. To apply mathematical programming techniques to the problem of optimal location and sizing of DG, it is necessary to use linearization or approximations to the equations in the balance of power.

Metaheuristic optimization techniques have been widely used in the location and design of the DG. These techniques include genetic algorithms, tabu search and colonies of particles. In [1] a model of multi-objective optimization was presented to determine the location and optimal sizing of DG using the technique of simulated annealing. The elements were modelled power losses, the number of generators, the voltage profile and power injected by the DG. The method sought a solution that would improve the voltage profile and reduce losses to the minimum DG units in the system. In [13] the authors presented a population-based metaheuristic based on the parasitic reproductive behaviour of some species of cuckoos (cuckoo search algorithm) for the location and optimal sizing of DG. The advantage of this algorithm was that it required a few parameters to calibrate. The aim of the study was the reduction of active power losses.

Hybrid methods combine two or more search techniques in order to exploit their potential and compensate for their deficiencies. The most common methods combine population hybrid techniques with methods that enhance some kind of local search or alternatively, heuristic methods with classical mathematical programming. In [3] a combination of simulated annealing and genetic algorithms for optimal location of DG comes with network distribution. The objective was to minimize losses. This shows that the combination of GA with simulated annealing was more effective than using only GA. In [11] a method to maximize the benefit to network operators and owners of distributed generation in a deregulated electricity market hybrid algorithm was presented. As well as simultaneously optimizing the benefits to the distribution company and to the owner of the DG their method also considered the uncertainty of demand and energy prices [20].

In [13] a hybrid algorithm was presented that improved stress profiles and reduced emissions using a particles' gravitational colony search to determine the proper location and sizing of the DG that minimized loss. The aim of this article is to contribute to the discussion on the effectiveness of heuristic and metaheuristic methods for optimal dimensioning and location of DG. Four different techniques were implemented and compared, namely i) simulated annealing, ii) variable search environment, iii) genetic algorithm and iv) a hybrid method that combines variable search environment with a genetic algorithm. To test the efficiency of these methods, they were applied to various tests in a distribution system (34 bars) that is widely used in the technical literature.

2. Background Mathematical Formulation

The objective function of the proposed problem is to improve the voltage profile and reduce system losses. To this end the indexes defined in [2] described below are taken. The rate of voltage profile, denoted as IPT, is defined by equation (1). This index takes into account the voltage and the bars and load expressed as Power of the system as a load factor. This makes it more important to maintain proper high-voltage in bars under higher demand.

$$IPT = \sum_{\{i=1\}}^{N} = V_{iL_i} \tag{1}$$

Variables: V_i: High-voltage in the bar i (p.u); L_i: Load in bar i (p.u); and N: Total number of bars. The rate of improvement of voltage profile, denoted as IMPT is given by the equation (2).

$$IMPT = \frac{IPT_{\{wDG\}} - IPT_{\{woDG\}}}{IPT_{\{woDG\}}} \; x\ 100 \tag{2}$$

Variables: $IPT_{\{wDG\}}$ is the index of the system voltage profile with DG (p.u.) and $IPT_{\{woDG\}}$ is the profile index stress the system without DG (p.u.). Note that the IMPT denotes the percentage improvement in IPT with DG. The second objective is to reduce active losses and compare losses with the system with and without DG, given by the equation in (3).

$$IPL_{\{wDG\}} = \sum_{\{K=1\}}^{N} I^2_{\{K,wDG\}} \, R_k * D_k + \, LL_{\{wDG\}} \quad (3)$$

A similar expression can reflect *woDG* conditions. The equation variables are described as follows:
$IPT_{\{wDG\}}$: Index line losses with DG.
R_k: Resistance in line K (p.u / km)
D_k: Length in line K (km).
$I^2_{\{\mathrm{K},wDG\}}$: Current line K with DG (p.u).
$LL_{\{wDG\}}$: Index line losses with DG.
$LL_{\{woDG\}}$: Index line losses without DG.
$I^2_{\{K,woDG\}}$: Online K stream without DG (p.u).

While the percentage reduction in losses in the line is income tax is given by equation (4):

$$IRPL = \frac{IPL_{\{wDG\}} - IPL_{\{woDG\}}}{IPL_{\{woDG\}}} \; x \, 100 \quad (4)$$

The objective function is to minimize the reduction rates of losses and to improve the voltage profile. In this case you should be using weighting factors W_1 and W_2 dimensions for each rate in order to assess their importance in the optimization process. To be noted, for maximizing the voltage profile can be achieved by equation (2) and set by the objective function from an equation (1). For minimizing the voltage profile can be readily available from the equation (4) and it can be by the objective function from an equation (3). Both the voltage profile cases the objective function can be determined from equation (1) for equation (3).

The optimization problem to solve is described by expressions form (5) to (17).

$$f(x) = W_{1IRPL} + W_{2IMPT} \quad (5)$$

Where the subject of the previous equation is:

$$0 \le W_m \le 1; \; m = 1{,}2 \quad (6)$$

$$\sum_{\{m=1\}}^{2} W_m = 1 \quad (7)$$

$$u_i P_{Gi} - P_{Di} - \, V_i \sum_{k=1}^{nb} [V_k(g_{ik} \cos\theta_{ik} + b_{ik} \sin(\theta_{ik}))] = 0 \quad (8)$$

$$u_i Q_{Gi} - Q_{Di} - \, V_i \sum_{k=1}^{nb} [V_k(g_{ik} \sin\theta_{ik} + b_{ik} \cos(\theta_{ik}))] = 0 \quad (9)$$

$$P_{ik} = V^2_{ig_{ik}} - \, V_i V_{kg_{ik}} \cos(\theta_{ik}) - \, V_i V_{kB_{ik}} \sin(\theta_{ik}) \quad (10)$$

$$Q_{ik} = V^2_{ib_{ik}} - \, V_i V_{kg_{ik}} \cos(\theta_{ik}) - \, V_i V_{kB_{ik}} \sin(\theta_{ik}) \quad (11)$$

$$S^2_{ik} = P^2_{ik} + Q^2_{ik} \quad (12)$$

$$P^{\min}_{Gi} \le \, V_i \le \, P^{\max}_{Gj} \quad (13)$$

$$V_i^{min} \le V_i \le V_i^{max} \quad (14)$$

$$S_{ik} \le S_{ik}^{max} \quad (15)$$

$$N_{DG} \le \, N_{DG}^{max} \quad (16)$$

$$u_i \in \{0,1\} \quad (17)$$

Where $P_{\{Gi\}}$ and $Q_{\{Gi\}}$ are the active and reactive power respectively, delivered by a unit of DG if it is located in the bar *i*. Note that not all bars have DG. DG for each unit must be assigned to a binary variable (called u_i). For simplicity, it is not considered that the DG inject or take reactive power from the network, so $Q_{\{gi\}} = 0$. $P_{\{DI\}}$ and $Q_{\{DI\}}$ correspond to power demands active and reactive bar i, respectively. Also nb is the number of bars, $\theta_{\{ik\}}$ is the angular opening between the bars and k; $g_{\{ik\}}$, and $B_{\{ik\}}$ are the real and imaginary, respectively, of the nodal admittance matrix parts. Constraints (8) and (9) represent the balance equations and reactive power, respectively. Restrictions (10), (11) and (12) represent the equations of active power flow, reactive and apparent power, respectively. The restrictions (13), (14) and (15), consider the power limits injected by the DG, limits voltage network and load flow limits, respectively. The constraint (16) indicates the maximum number of units DG needs to consider and restriction (17) indicates the binary nature of the variables u_i (1 if with DG and 0 if without DG).The model described by equations (5) - (17) corresponds to a problem in mixed integer nonlinear programming which is highly dimensional and non-convex having multiple local optima, which justified its solution using the search methods illustrated in this article.

3. Methodology on Hybrid Optimization Algorithm

To address the problem of optimal location and the sizing of DG described in the previous section four techniques were used as combinatorial optimization: Simulated Annealing, Variable Descending Search Environment, Genetic Algorithm and Hybrid Genetic Algorithm. A brief description of each technical solution as adopted in this study is presented.

3.1. Simulated Annealing

Simulated Annealing (SA) emulates the annealing process in steel and ceramics, which involves heating and then slowly cooling the material to vary its physical properties. This procedure was introduced in [9]. In each iteration of the SA some neighbours of the current status are evaluated and probabilistic decision made between making the transition to a new state or remaining in the current state. If the neighbour solution enhances the value of the objective function is accepted with probability 1, otherwise the probability of accepting by the Metropolis criterion given by equation (18) where the parameter c corresponds to the temperature.

$$Prob(accept\ \acute{x}) = \begin{cases} 1 & , f(\acute{x}) < f(x) \\ \exp\left(-\dfrac{f(\acute{x}) - f(x)}{c}\right) & , f(\acute{x}) \geq f(x) \end{cases} \tag{18}$$

SA assesses unattractive solutions in the early stages, then as the temperature parameter is reduced, the search becomes more selective, lessening the declines in the objective function.

3.2. Variable Search Environment Descending

Environment Variable Search (EVS) is a metaheuristic based on a local search in a changing neighbourhood (also known as environment structure) [17]. Variations in EVS are given the names *down, reduced, basic* or *genera*l EVS. This paper considered an extension of EVS known as Variable Search Environment Descending (VSED) in which the current solution obtained from the change in a local search is implemented; as long as this one has found a better solution. VSED is illustrated below [4] as the following:

- Initialization: Select the set of environments, structures $N_k, k = 1,..,\mathrm{k}_{\max}$ to be used in the descent. Find an initial solution x;
- Iterations: Repeat until no improvement is obtained (until there is no more optimization that we can get).

In the following sequence:

(1) Make $k \rightarrow 1$.

(2) Repeat until $k = k_{max}$ the following:
   (a) Exploration of the environment: Find the best solution x' of the k^{th} neighborhood of $x(x' \in N_k(x)$
   (b) Move or not: If the obtained solution x' is better than x, do $x \rightarrow x'$, $k \rightarrow 1$; otherwise do $\rightarrow k + 1$.

In the study presented in this article, environments or neighbourhoods were defined as the size (increase or decrease the capacity of the DG) and location (DG move to a neighbouring node).

3.3. Genetic Algorithm

Genetic Algorithms (GA) solve optimization problems by simulating natural selection or "survival of the fittest" [10]. The general routine of a GA is to generate an initial population of random or pseudo-random solutions. Each individual in the population is defined by a string of bits. In this case, the objective function is to evaluate the power flow as a consequence of the location and sizing of the DG [18]. For a given tournament a number of individuals are selected. The number of tournaments is equal to the size of the population. Recombination is made at one randomly selected point. The mutation is created by changing a bit (zero to one) randomly with a given probability of occurrence. Individuals generated in the process of recombination and mutation replaces existing individuals if they are better than their predecessors. Two stopping criteria are considered; the maximum number of iterations or the maximum number of iterations without improvement of the objective functions.

.3.4. Hybrid Genetic Algorithm

Hybrid methods (HGA) seek to combine the advantages of two or more metaheuristics for high quality solutions. The most common hybrid methods combine population methods (e.g. Genetic Algorithms) with local search methods (Simulated Annealing, Variable Search Environment) or exact methods (linear programming, nonlinear) [16]. In this paper a method population (GA) combined with a local search method (VSED) was implemented. The flowchart of the implemented algorithm is illustrated in Fig.1 below. The HGA structure retains essentially the GA structure described in the previous section; however, after mutation and before replacing the individuals of the next generation it performs a local search in order to find better quality individuals in the current generation [19]. As already described in the GA, only individuals exhibiting improvement in the objective function are included in the new generation.

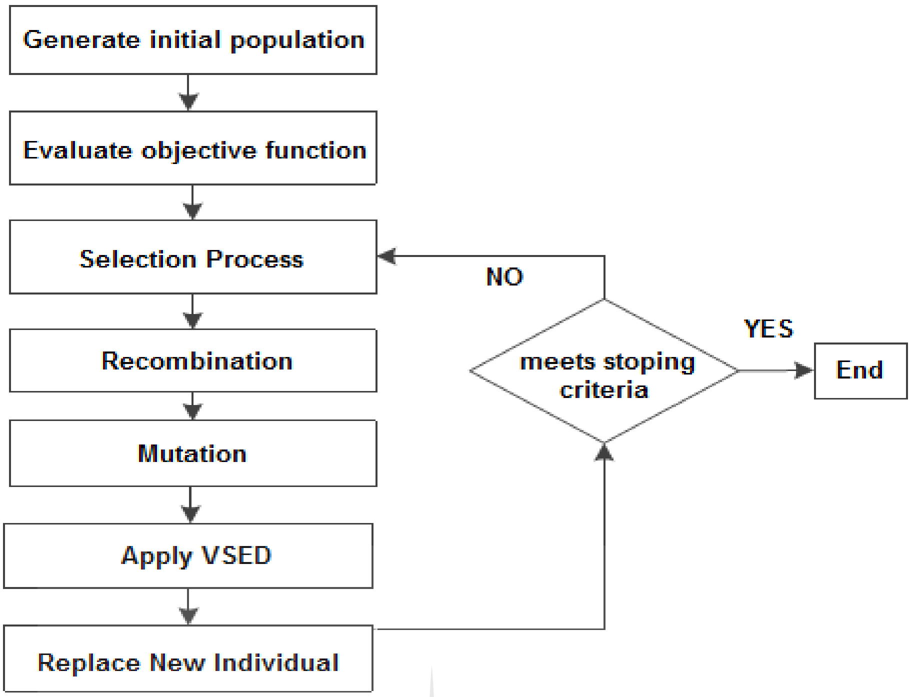

Figure 1: Diagram of HGA Algorithm.

4. Numerical Simulation Test and Investigation Results

In Fig. 2 a distribution system of IEEE standard 34 bars is illustrated. The maximum network demand is 15,8 MW with a power factor of 0.95 lag. It may include up to 4 DG units, each one represented with a maximum power of 2.0 MW. Candidate solutions with DG units are penalized in the objective function (to minimize the loss in power) in order to make them less attractive. Note that according to the formulation (equation (17)) the algorithm may select other number DG units up to the maximum.

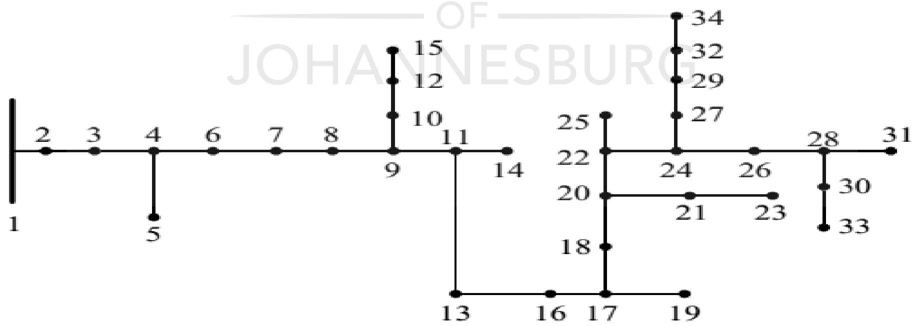

Figure 2: Distribution System of 34 bars.

The distribution of demand in each of the network nodes is shown in Fig. 3. It can be seen that a significant part of the demand is in the first bars.

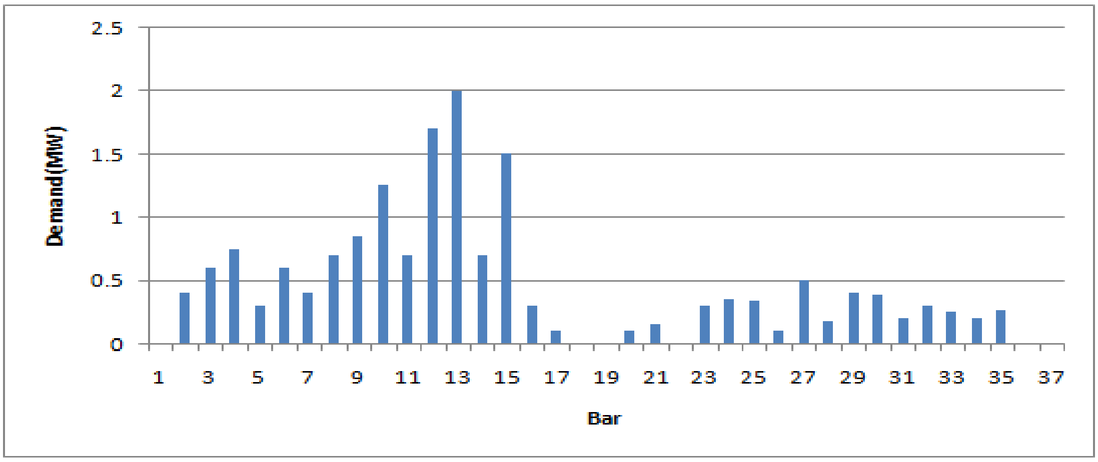

Figure 3: Distribution of demand in the system of 34 bars.

.4.1. Coding Solutions

Table 1: Codification of DG size.

Code	Size(MW)	Code	Size(MW)
1000	0.25	1100	1.25
1001	0.50	1101	1.50
1010	0.75	1110	1.75
1011	1.00	1111	2.00

A chain of 4 binary bits was used to represent each used generator. The first bit represented the state of the generator (generator 1, the generator does not exist 0); the remaining 3 bits represented the power level of the generator. Thus, 1000 denoted minimum capacity (0.25 MW), while the chain 1111 represented a generator with maximum capacity (2.0 MW). Table 1 illustrates the equivalence. Table 2 illustrates the code of a particular candidate solution comprising 4**nb* bits, where *nb* was the number of bars in the system. Bars 1, 2, 4 and *nb*-1 have no generator; while bars 3 and *nb* have generating capacities of 1.0 and 2.0 MW, respectively.

Table 2: Solution candidates encoding.

Bus1	Bus2	Bus3	Bus4		Bus nb-1	Bus nb
0100	0011	1011	0111	……..	0011	**1111**

.4.2. Weighted Factors Calibration

Before starting the optimization process weighting factors must be assigned to the two objectives under study (IRPL and IMPT) in order to assess the relative fitness of particular solutions. This requires a diagnosis without DG base case. This diagnosis was made by a load flow calculation with and without DG. The load flow analysis was performed by software Matpower [15] with DG modelled as bars where active power could be injected. In Fig. 4 and Fig. 5, the voltage profile and line losses, respectively, with and without DG are illustrated.

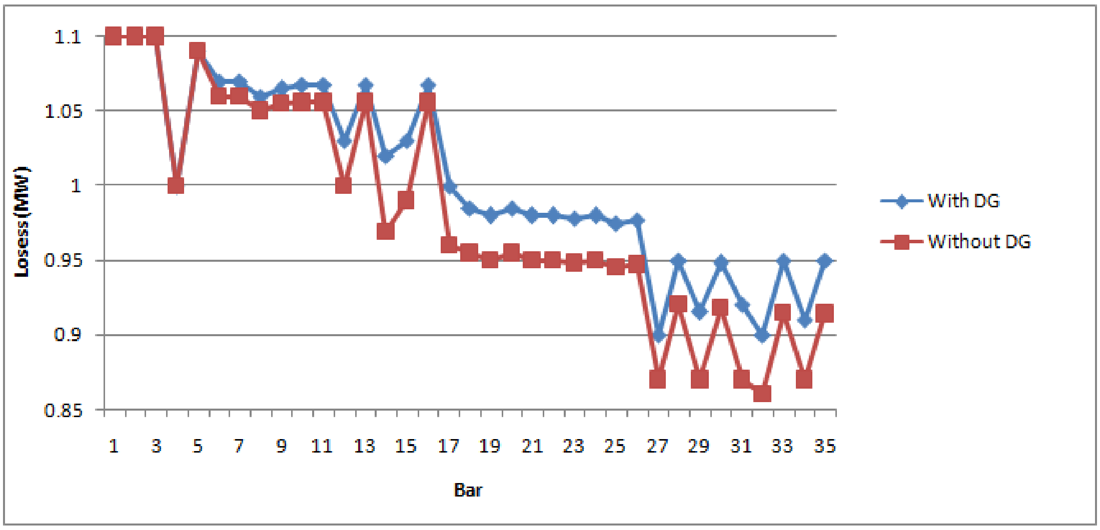

Figure 4: Voltage profile system of 34 bars with and without DG.

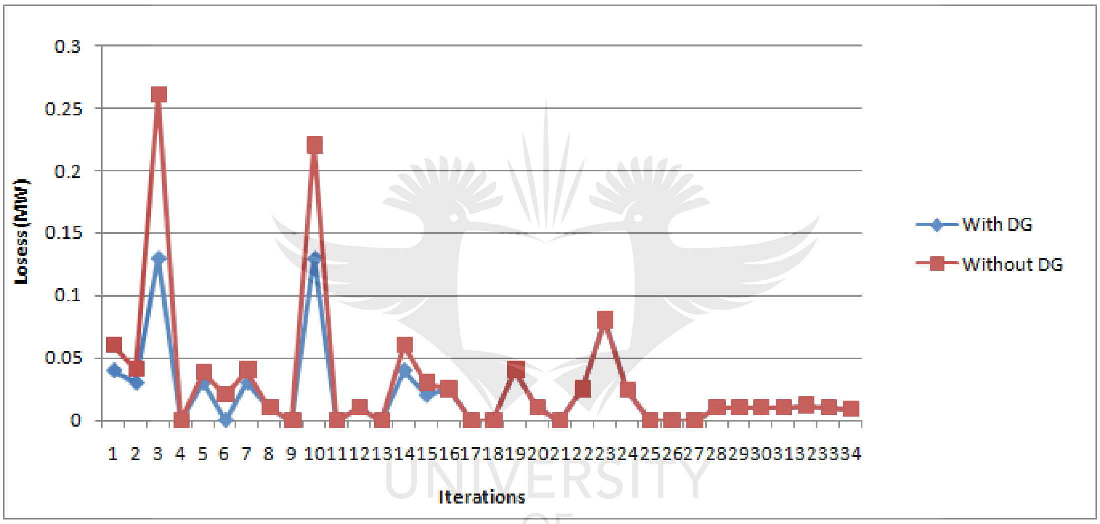

Figure 5: Line losses of 34 bar system with and without DG.

Table 3: Values of IRPL and IMPT for candidates with randomly generated solutions.

Simulation	IRPL	IMPT	IRPL/IMPT
1	41,884	1,513	**27,682**
2	50,127	2,806	**17,864**
3	43,297	2,124	**20,385**
4	57,487	2,478	**23,199**
5	34,329	1,878	**18,280**
6	30,287	1,079	**26,070**
7	44,238	2,567	**17,233**
8	30,234	1,969	**15,355**

A case with 4 units of DG is illustrated; each with 1 MW located in the bars 5, 10, 15 and 20. In Fig. 4 it may be noted that even adjusting the tension in the substation at 1.1 p.u., when DG were not tensions, the last bars were below 0.9 p.u. featuring voltage regulation (percentage difference between the maximum and minimum system voltages) exceeding 20%. However, when DG was introduced to the system stresses increased, especially in remote substation busbars, causing the voltage regulation in these rods to fall to 17.5%. On the other hand, total losses without DG amounted to 959.5 kW systems and with DG were 555.8 kW. When calculating indices IMPT and IRPL by the expressions (2) and (4) respectively values obtained were IMPT = 1.5135 and IRPL = 41.8848. These indices were calculated for different solution candidates (location and DG sizing) randomly generated resulting in the data given in Table 3. It can be seen that IRPL was much higher than IMPT in all simulations. This was because the percentage of loss reduction was more significant than the improvement in voltage profile. On average, IRPL was about 20 times greater than IMPT as seen in the fourth column of Table 3. If the indexes were optimized without using weighting factors that would favour solutions that reduced losses in order to improve tensions. Weighting factors $w_1 = 0.05$ and $w_2 = 0.95$ were assigned in order to give similar importance to IMPT and IRPL objectives in the optimization process. However, the manager of the planning system can select other values to give more importance to a particular target.

.4.3. *Results using Simulated Annealing*

To start the SA, a base solution that meets the criterion of maximum number of generators is generated. From there neighbouring solutions are explored according to the criteria stated in equation (18). This means that early in the process the probability of accepting poorer quality solutions is high, but as the process evolves that probability is restricted. Thus, the principle of seeking diversity is privileged and at the end of the simulation it intensifies the search for better solutions. After performing several trial runs with different SA algorithm parameters, initial and final temperature was calibrated at 3.0 and 0.5, respectively, and at each iteration the temperature was reduced by 0.01. In Table 4 and Fig 6 the best solution found (after 190 iterations) and the convergence of the algorithm illustrated by the SA. In this case the time for calculation was 1.2 minutes. A computer Intel Core i3 2.4 GHz with 4 GB of RAM was used in all simulations.

Table 4: Best result using SA.

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
8	1,5	2,9578	4,3747	7,3325
17	1,75			
22	2			
29	1,5			

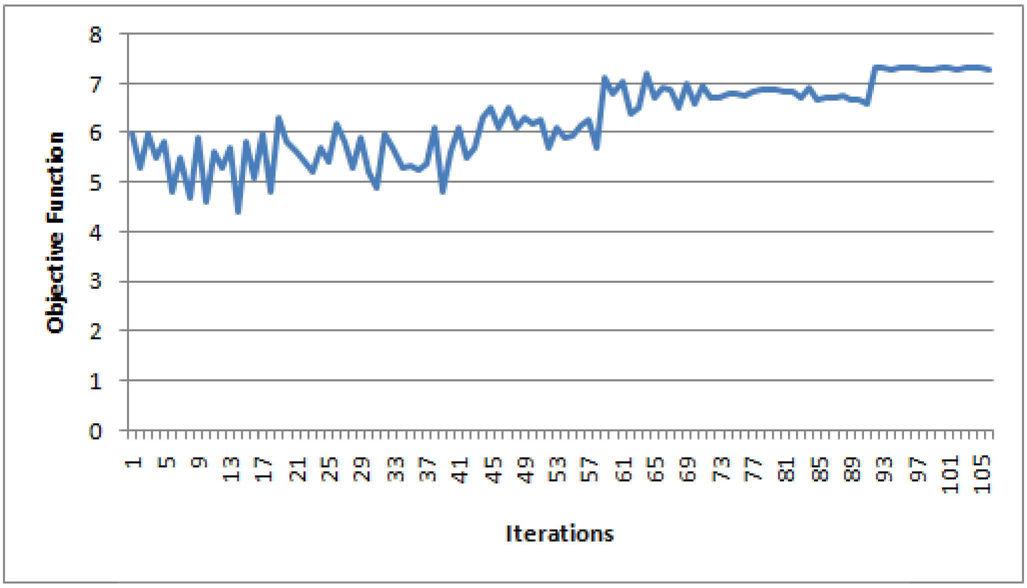

Figure 6: Convergence process in SA.

4.4. Results using Variable Search Environment Descending

The size and location of the DG defined the VSED environment. A base solution of individuals was explored to better the environment by following the instructions as described in the methodology section. The search continues until it either passes a certain number of iterations or until no improvement is achieved over previous iterations. In Table 5 the best found VSED is illustrated. Here 22 iterations were performed by evaluating the structure of 8 individuals with a computation time of 2.1 minutes.

Table 5: Best result using VSED.

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
5	2,0	3,9274	3,8313	7,7857
10	2,0			
21	1,5			
31	1,5			

4.5. Results using the Genetic Algorithm

The implemented GA solution used a coding chromosome structure as illustrated in Table 2. An initial population of possible solutions was generated pseudo-randomly which led to new solutions of better quality achieved by implementing a sequence of selection, recombination and mutation as described in the methodology section. The GA parameters of initial population size, mutation rates and recombination were calibrated through repeated runs. It was noted that with small initial populations, poor quality responses were obtained. By increasing the number of individuals in the initial population the quality of solutions improved, but the computing time increased. The best solution was found with a population of 100 individuals and mutation and recombination rates of 10% each. The computation time to find the best solution was 2.9 minutes after 90 iterations. The best result is shown in Table 6 while Fig. 7 shows the process of convergence for different tests. It can be seen that even though the initial populations were of different quality, the tests converged to solutions of similar quality.

Table 6: Best result using GA.

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
10	2,5	3,8887	3,7836	7,6723
15	1,5			
26	1,5			
29	1,25			

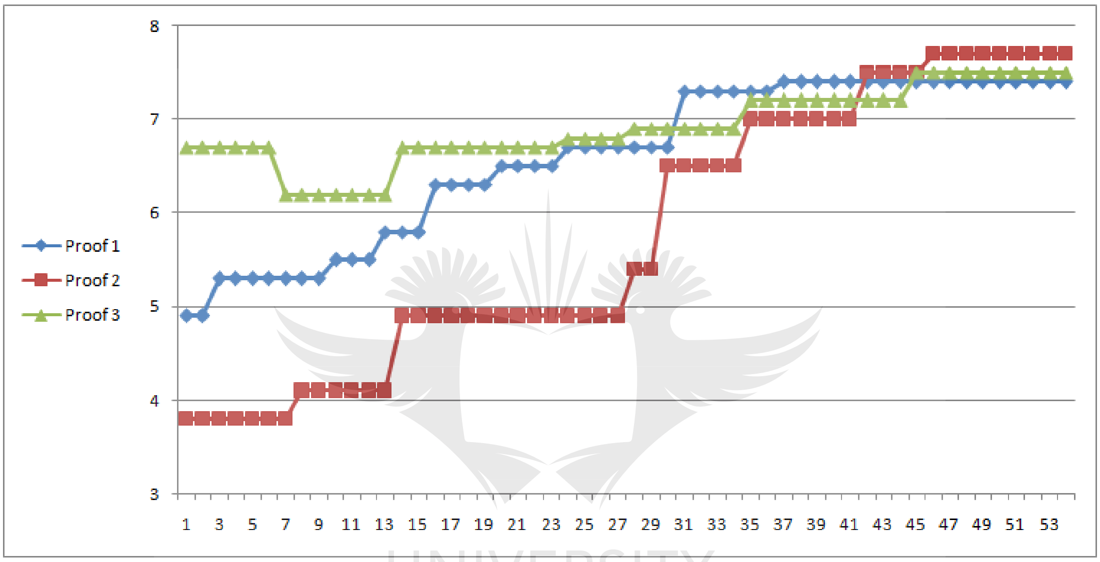

Figure 7: Process of convergence for 3 different GA tests.

.4.6. Results using the Hybrid Genetic Algorithm

Table 7: Best result using HGA.

Bar	Size (MW)	w_1IRPL	w_2IMPT	FO
12	1,7	4,0573	3,9201	7,9774
13	2,0			
22	1,0			
30	1,25			

As mentioned above the HGA implemented combined the GA described in the previous section with VSED. That is, after applying the traditional operators of GA and prior to the population replacement in each iteration, the fitness of individuals was increased using VSED. The same parameters were calibrated as for with traditional GA. Table 7 presents the best solution found. It was observed for all tests that the computational time was considerably greater than that required by the other algorithms implemented; however, the quality of the response was better. The best answer was found after only 6 iterations in a computation time of 12.6 minutes.

5. Compartative Performacne Index of Algorithms

The best result was obtained using HGA; however, this is the method that took longer to find a high quality solution. The fastest converging test algorithm was the simulated annealing, but solutions obtained with the other methodologies were of better quality. The VSED required less iteration to converge compared to the SA, but it's computing time per iteration was greater and to be evaluated in terms of iteration, two structures of the neighbourhood were needed. HGA generated the highest quality solutions when using large initial populations of 100 individuals. Fig. 8 compares the computation time for the methods used, where the HGA stands out as relatively slow. The best solution found (see Table 7) showed an 80.2% reduction in losses compared to the base case without DG.

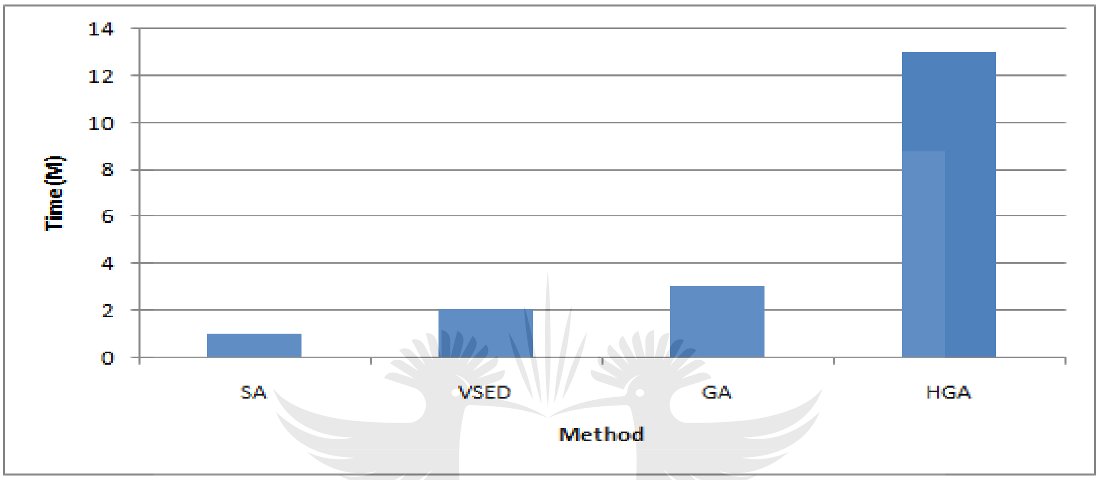

Figure 8: Search time comparison.

6. Conclusion

In this study, four algorithms were compared to obtain the optimum location and sizing of DG in distribution systems: SA, VSED, GA and HGA. The implemented methodologies based on these optimization algorithms were all successful in finding high quality solutions. In the trialled application tests the best results were obtained using HGA, which combines genetic algorithm and VSED. It was observed that the optimum percentage of DG penetration of the test system varied between 6 and 7 MW installed at the start bar and the end bar for substantial improvement using DG units of 1-2 MW. In addition, the optimum location and sizing for DG allowed a substantial improvement of the voltage profile of the network and reduced losses of 80.2 per cent in the test system. Regarding computation times, the fastest method was SA; however VSED and the HGA showed better results.

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