

**OPTIMIZATION OF PLACEMENT AND SIZING OF
DISTRIBUTED GENERATION AND CAPACITORS FOR
VOLTAGE STABILITY IMPROVEMENT**

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**Optimization of Placement and Sizing of Distributed Generation and
Capacitors for Voltage Stability Improvement**

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**A thesis submitted in partial fulfillment of the requirement for the
degree of Master of Science in Electrical Engineering in the Jomo
Kenyatta University of Agriculture and Technology**

2021

DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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This thesis has been submitted for examination with our approval as University Supervisors

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DEDICATION

To my wife and daughters,

ACKNOWLEDGEMENT

I wish to acknowledge the efforts of my supervisors for guiding and encouraging me through this research. I would also like to thank the Postgraduate students of JKUAT for their insights geared towards the completion of this work.

ABSTRACT

Distribution systems form a critical part of the power system by linking the consumer to the transmission system. They are extensive and complex and require adequate planning. One of the main challenges in distribution networks is voltage instability. Voltage instability can be mitigated by distributed generation (DGs) and capacitor placement in distribution networks. The effectiveness of these devices is much dependent on how optimal they are placed and sized within the distribution network. Due to the complexity of distribution networks, planning becomes a complex task. Therefore, new techniques must be developed to assist network planners in optimally placing and sizing capacitors and DGs in distribution networks. In this work, a method for distributed generation and capacitor placement was developed that uses Voltage Stability Index (VSI) to find optimal locations of distributed generation and capacitors and Hybrid Evolution Programming (HEP) to find the optimal sizes of DGs and Capacitors that maximize the voltage stability of a radial distribution network. The test networks used were IEEE 33-bus and IEEE 69-bus radial distribution networks. The voltage profiles and VSIs for the radial distribution systems were compared using optimal sizes obtained from Evolution Programming (EP) and the developed Hybrid Evolution Programming (HEP) Algorithm. The minimum voltage obtained after placing DGs and capacitors using EP in the IEEE 33-bus radial distribution network was 0.9290p.u, whereas the minimum VSI was obtained as 0.7480. When HEP was used, the minimum voltage was 0.9400 p.u. with a VSI of 0.7841. Placing the DGs and Capacitors in the IEEE-69 Bus system resulted in a minimum voltage improvement from 0.8750p.u to 0.9480 p.u., and VSI improvement from 0.5889 to 0.8077. Network modeling and simulations were performed in MATLAB.

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LIST OF ABBREVIATIONS

BCBV	Bus Current to Bus Voltage
BIBC	Bus Injection to Bus Current
DG	Distributed Generation
EP	Evolution Programming
FACTS	Flexible Alternating Current Transmission
GA	Genetic Algorithm
HEP	Hybrid Evolution Programming
MINLP	Mixed-Integer Non-Linear Programming
PSI	Power Stability Margin
P-V	Active Power-Voltage
PoVC	Point of Voltage Collapse
Q-V	Reactive Power-Voltage
SA	Simulated Annealing
TS	Tabu Search
VAR	Volt-Ampere Reactive
VSI	Voltage Stability Index
VSM	Voltage Stability Margin

CHAPTER ONE

INTRODUCTION

1.1 Background

The power system network comprises four essential segments: generation, transmission, distribution, and utilization. These segments must be planned and operated securely to maintain a given frequency and voltage level. Traditionally, the voltage in distribution systems is controlled and kept within a specified range using various devices such as static VAR compensators and on-load tap changers. The operation of these devices is usually co-ordinated to ensure proper operation (Hadjsaïd & Sabonnadière, 2013).

In the recent past, electric power demand has dramatically increased due to increasing population and rapid economic growth, especially in developing regions. It has resulted in distribution systems being operated close to their maximum voltage stability and power carrying capacity limits. Further, distribution systems are changing from passive networks to active networks due to the proliferation of distributed generation (Hashim et al., 2012). The increased addition of distributed generation comes with many adverse effects. The effects include voltage variations, degraded protection, altered transient stability limits, bidirectional power flows, and increased MVA fault level. Voltage variation has been addressed as the most dominant impact of distributed generation (Xu & Taylor, 2008).

Voltage stability is a requirement for the secure operation of distribution systems. Planning of Distributed Generation and their control strategies have a bearing on the distribution system's voltage stability situation (Atwa et al., 2010; Hu et al., 2015). The planning aspect involves proper location and sizing of the distributed generation and other reactive power sources in the distribution network. In contrast, the control aspect involves the co-ordinated operation of these DGs and conventional voltage and reactive power devices (Sarmin, 2013).

With the increased use of Distributed Generation, it has become critical to incorporate them in distribution system planning. The distributed generation placement problem has been a crucial area of research in the recent past. Different researchers have addressed the distributed generation problem in different ways. The objective functions used by researchers in distributed generation planning include power loss minimization, reliability enhancement, minimization of operational and investment cost, and voltage stability enhancement (Georgilakis & Hatziargyriou, 2013). The objective function used in this research is maximizing voltage stability.

Many methods have been employed by researchers in DG and capacitor placement problems. These methods include analytical methods, numerical methods, and heuristic methods. Heuristic methods have been found to work well for large and complex optimization problems such as DG and capacitor placement problem (Ai et al., 2014). Heuristic methods that have been used in DG and capacitor placement planning include particle swarm optimization (Antony & Baby, 2013; Jamian et al., 2012), bacteria foraging

algorithm (Mohamed Imran A & Kowsalya M, 2014), differential evolution algorithm (Mohapatra et al., 2012), and ant colony algorithm (Kasaei, 2014). However, these individual search heuristics suffer poor local optimization when the size of the search space is large.

Therefore, it is common practice to use hybrid search heuristics to solve optimization problems to alleviate this problem. Hybrid search heuristic methods incorporate more than one search technique and draw the particular method's advantages, resulting in better search results. This research employs a hybrid algorithm that integrates Evolution Programming, Tabu Search and Simulated Annealing to find optimal sizes of capacitors and distributed generation placed at optimal locations for voltage stability enhancement.

1.2 Problem Statement

Power distribution systems are becoming increasingly saturated and are being operated close to voltage stability and power transfer capability limits. This has resulted from the growth in consumption and geographical and environmental concerns making it difficult to construct new lines and power plants that would otherwise relieve these strained networks. Also, there has been a proliferation of distributed generation in distribution networks, driven by the need to lower carbon emissions caused by fossil fuels. The addition of distributed generation has presented technical and operational challenges such as a rise in voltage levels, equipment thermal ratings, and protection issues.

The dominant effect of increased DG penetration is voltage instability. This problem can be addressed by optimal planning and operation of distributed generation together with conventional voltage and reactive power control devices in distribution networks. The planning aspect involves optimal sizing and placement of DGs and reactive sources such as capacitors.

1.3 Justification

The rise in the use of distributed generation in distribution networks has presented utility companies with both benefits and challenges. The trade-off lies in the optimal placement of these DGs and conventional voltage support components such as capacitors within the distribution network. Utilities require the use of the most effective tools and techniques to help them optimally place these components.

Due to the complexity and magnitude of the DG and capacitor placement problem, there is a need to use techniques that automate the solution process. Many commonly used solvers, such as Linear programming, when used in large scale optimization problems, lead to substantial computational effort with a high risk of lack of convergence. Also, the programming effort required when using the classical technique is considerable. Heuristic search techniques are increasingly being used to solve optimization problems because they are easy to adapt to a wide range of problems while at the same time requiring less computational and programming effort. Heuristic methods have also give fairly optimal results with minimal computation.

These heuristic methods continue to be developed through hybridization between them to combine their strengths and achieve better results than when using individual methods. The employed hybrid algorithm offers the following benefits over individual search methods:

- a) The algorithm divides the search space into different sub-populations. A unique mutation operator is used to search each sub-population to enhance the search diversity and improves population evolution hence provide high-quality solutions than those of individual search techniques.
- b) Results of search from each subpopulation are combined to exchange search information, hence reducing chances of premature convergence caused by the consistency of individuals in a single population.
- c) The algorithm incorporates the probabilistic updating strategy of Tabu Search and annealing schedule of Simulated Annealing during the selection process to complement the use of fitness function and avoid being trapped in local minima.

1.4 Objectives

This section outlines the main and specific objectives of this work.

1.4.1 Main Objective

The main objective was to optimally place and size DGs and capacitors in radial distribution networks using Hybrid Evolution programming to improve voltage stability.

1.4.2 Specific Objectives

- a) To formulate an objective function based on voltage stability index for the optimization problem.
- b) To perform load flow analysis of IEEE 33-Bus and IEEE 69-bus radial distribution systems and determine the weak buses most likely to suffer voltage instability by determining the Voltage Stability Index of each bus.
- c) To search the optimal sizes of DGs and capacitors that will simultaneously be placed at the identified weak buses to optimize the formulated objective function, using Evolution Programming and Hybrid Evolution Programming.
- d) To evaluate the performance of the Hybrid Evolution Programming method.

1.4.3 Scope

The scope of this research entails the use of the Voltage stability index advanced by (Chakravorty & Das, 2001) in determining the optimal location of DGs and Capacitors in distribution networks. Radial distribution networks were considered in this work. Also, only Type one DGs, and static capacitors were considered in this work. Simulations were done in MATLAB. The proposed algorithm was tested using the reduced IEEE 33-Bus and IEEE 69-Bus radial distribution networks.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

This chapter reviews the subject of voltage stability in power systems and methods of its determination. Further, power flow methods in power system networks were reviewed, and their applicability in radial distribution networks. This chapter also examines the subject of distributed generation in terms of various definitions, classifications, and characteristics. The chapter finally critically reviews optimization methods applied by researchers to place and size distributed generation and static capacitors in power system networks and the objective functions these researchers used.

Based on this review, this work used the voltage stability index as the objective function and the Backward and Forward sweep as the power flow method. This work also used a hybridized method comprising Evolution Programming, Tabu Search, and Simulated Annealing, to optimally place and size Type I DGs together with static capacitors in radial distribution networks.

2.2 Voltage Stability: Definition and Methods of its determination

Voltage stability is the ability of a power system to sustain acceptable voltage levels under normal operating conditions and after a disturbance (Viawan, 2008). Voltage instability is caused by the mismatch between the reactive power generated and that consumed. Reactive power is supplied in a power system by generators or reactive power

compensators such as capacitors. Instances that cause voltage instability include increment in load, power system faults, and exceeding the generators' reactive power limits (Modarresi et al., 2016).

Voltage instability can lead to stalling of induction motors when the voltage drop causes an imbalance between the electrical torque and mechanical torque, causing the induction motor to decelerate and eventually stall. The reason for stalling is that an induction motor's electrical torque is directly proportional to the square of the applied stator voltage. Also, voltage instability may cause transient overexcitation of synchronous machines near the area where the voltage instability occurs. During voltage instability, the synchronous generator's rotor current may exceed the limit allowed by the overexcitation limiter. Breaching this limit triggers generator protection to kick in, causing the synchronous machines to lose synchronism, hence a local blackout (Potamianakis & Vournas, 2006). Voltage instability is mitigated by voltage support using distributed generation and capacitors, FACTS devices, and load shedding.

Voltage stability is usually analyzed by the use of P-V curves, Q-V curves, and stability indices. In the P-V curve method, real power at a bus is gradually increased by keeping the power factor constant. Repeated power flow studies are done until the Point of Voltage collapse (PoVC) is obtained. PoVC is the nose of the P-V curve. An increase in load beyond the PoVC will lead to a rapid voltage drop of the power system and, consequently, voltage collapse or network collapse. Voltage collapse usually occurs at a heavily loaded bus in a power system with insufficient local reactive power sources at that

bus that supports the voltage and hence fails to provide a secure voltage profile for the system (Gupta & Gupta, 2015). Figure 2.1 represents the P-V curves for different loads.

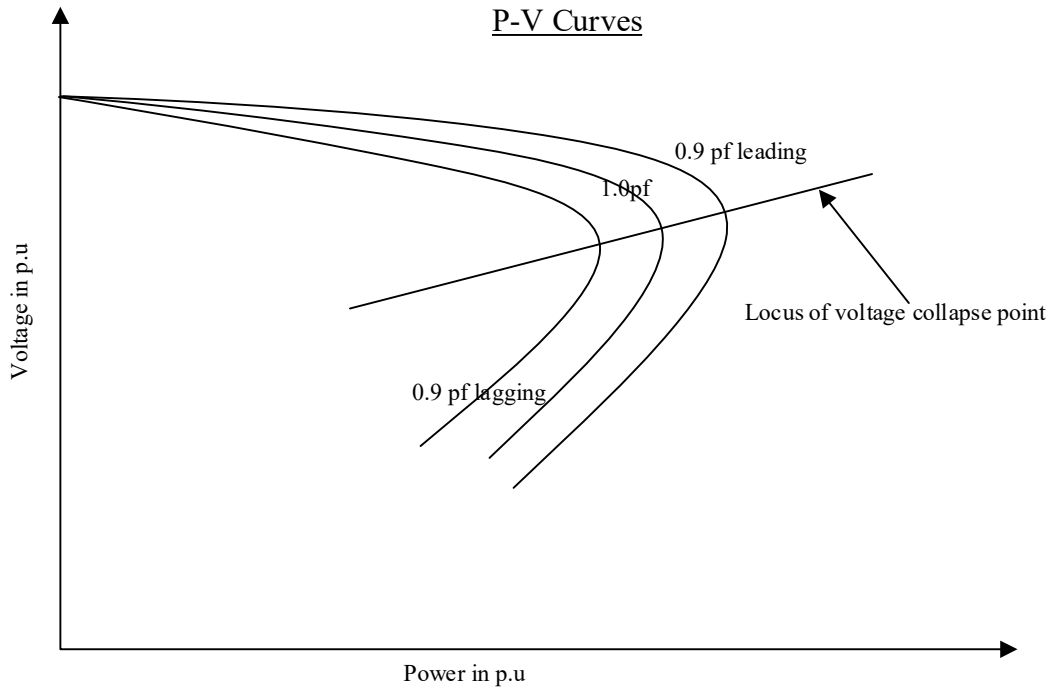


Figure 2.1: P-V Curves for different loads for different power factors.

Q-V curve method of voltage stability analysis shows the variation of receiving end voltage with variation in load reactive power for different real power loads, as shown in Figure 2.2. The region to the right of the locus of knee point represents the stable region. When using the Q-V method, the sensitivity of voltage to changes in reactive power at a given bus is given by the Q-V curve slope. If the bus's V-Q slope is positive, the system is voltage stable, and if negative, the system is voltage unstable. Other methods used for steady-state voltage stability analysis are modal analysis and sensitivity analysis.

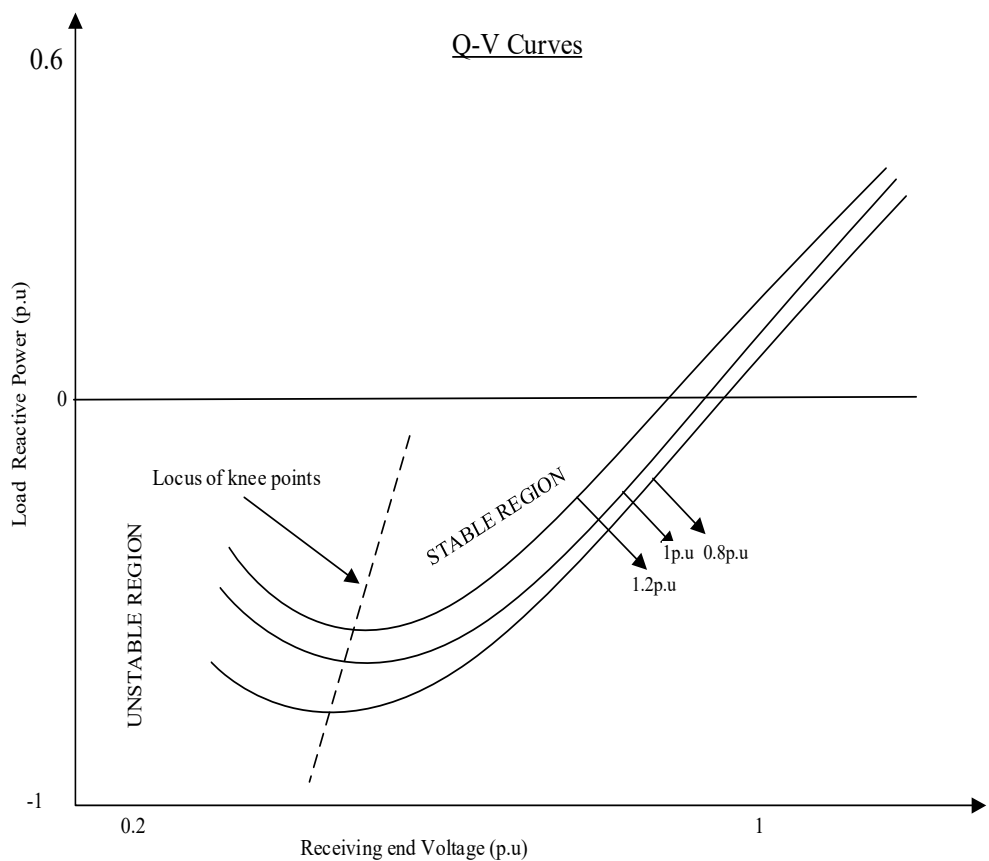


Figure 2.2: Q-V Curves for different real power loads.

These methods use the Power Flow Jacobian obtained by solving a set of equations linearized about a given operating point. The Jacobian is evaluated for singularity to determine the maximum loadability of the power system. The main disadvantages of these techniques are that they require considerable computation effort and are time-consuming, especially for an extensive network (Belhadj & Abido, 1999).

Researchers have recently developed indices for voltage stability analysis in power systems, particularly for the analysis of ring and radial distribution systems. Distribution networks are large and complex and require stability analysis tools that do not require

enormous computational effort. Many indices have been developed by researchers studying voltage stability of power systems as a measure of how far or near a system is from voltage instability or voltage collapse.

(Modarresi et al., 2016) gave a comprehensive review of voltage stability indices has been done. The authors have classified voltage stability indices into three categories: bus, line, and overall stability indices. Line voltage stability indices determine how close a line is from voltage collapse. The bus voltage stability indices determine the stability of system buses. The Overall Voltage Stability indices are not related to buses or lines. They are used to determine the system voltage collapse point. The Voltage Stability Index (VSI) presented in (Chakravorty & Das, 2001) was used in this work as the objective function. The index is simple and suitable for voltage stability determination in radial distribution networks. The VSI is formulated by equation (2.1).

$$VSI_i = V_s^4 - 4V_s^2(R_i P_{Li} + X_i Q_{Li}) - 4(X_i P_{Li} - R_i Q_{Li})^2 \quad (2.1)$$

where,

VSI_i is Voltage Stability Index at Bus i

V_s is distribution substation voltage which is 1 p.u

R_i is resistance between source bus and bus i

X_i is reactance between source bus and bus i

P_{Li} is the active power flow through bus i

Q_{Li} is the reactive power flow through bus i

2.3 Power flow methods for radial distribution systems

Power flow is an important process of determining power system parameters such as real power, reactive power, bus voltages, power angle, and line losses. This section outlines the power flow equations and power flow methods used to solve these equations.

2.3.1 Power flow equations

Distribution networks have a high R/X ratio and operate in unbalanced conditions. Also, distribution networks are increasingly becoming active due to distributed generation, and as such new techniques of load flows are being adopted. This section reviews various techniques that researchers have applied to solve load flows in distribution networks. The power flow equations that require to be solved by a load flow method are derived in this section.

Consider Figure 2.3 that shows two nodes of a distribution line.

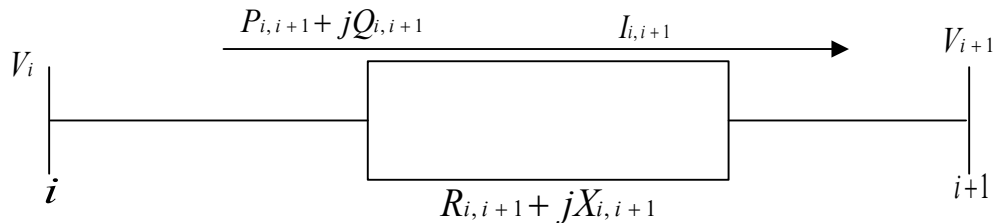


Figure 2.3: Representation of two nodes in a distribution network.

The power flow equations in the branch $i, i+1$ are given by equation (2.2) and equation (2.3):

$$P_{i,i+1} = P_{i+1} - \left(R_{i,i+1} \frac{P_{i,i+1}^2 + Q_{i,i+1}^2}{|V_i|^2} \right) \quad (2.2)$$

$$Q_{i,i+1} = Q_{i+1} - \left(X_{i,i+1} \frac{P_{i,i+1}^2 + Q_{i,i+1}^2}{|V_i|^2} \right) \quad (2.3)$$

The voltage at the node i is $V_i \angle \delta$

The voltage at the node $i+1$ is $V_{i+1} \angle \delta_{i+1}$

Consider the branch between i and $i+1$, where

$$I_{i,i+1} = \frac{V_i \angle \delta_i - V_{i+1} \angle \delta_{i+1}}{R_{i,i+1} + jX_{i,i+1}} \quad (2.4)$$

$$I_{i,i+1} = \frac{P_{i,i+1} - jQ_{i,i+1}}{V_i \angle -\delta} \quad (2.5)$$

By equating equation (2.4) and (2.5), the result becomes equation (2.6):

$$\frac{P_{i,i+1} - jQ_{i,i+1}}{V_i \angle -\delta} = \frac{V_i \angle \delta_i - V_{i+1} \angle \delta_{i+1}}{R_{i,i+1} + jX_{i,i+1}} \quad (2.6)$$

and upon cross multiplying, the result becomes equation (2.7):

$$V_i^2 - V_i V_{i+1} \angle \delta_{i+1} - \delta_i = (P_{i,i+1} - jQ_{i,i+1})(R_{i,i+1} + jX_{i,i+1}) \quad (2.7)$$

Equating real and imaginary parts on both sides of equation (2.7), we obtain equations

(2.8) and (2.9):

$$V_i^2 - V_i V_{i+1} \cos(\delta_{i+1} - \delta_i) = P_{i,i+1} R_{i,i+1} + Q_{i,i+1} X_{i,i+1} \quad (2.8)$$

$$V_i V_{i+1} \sin(\delta_{i+1} - \delta_i) = P_{i,i+1} X_{i,i+1} + Q_{i,i+1} R_{i,i+1} \quad (2.9)$$

Squaring and adding equations (2.8) and (2.9), we obtain equation (2.10):

$$V_{i+1}^2 = V_i^2 - 2(P_{i,i+1} R_{i,i+1} + Q_{i,i+1} X_{i,i+1}) + \frac{(P_{i,i+1} R_{i,i+1} + Q_{i,i+1} X_{i,i+1})^2}{V_i^2} \quad (2.10)$$

Equations (2.2), (2.3), and (2.10) are the power flow equations that are solved recursively by power flow methods discussed in sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, and 2.3.6.

2.3.2 Forward and Backward Sweep Method

This method has been used by (Rupa & Ganesh, 2014) to solve load flow for the IEEE-33 bus radial distribution system. It involves two steps, which are done iteratively, namely forward sweep and backward sweep. In the forward sweep, voltage drop calculation is done. Also, power flow and nodal voltages are updated in a forward direction, starting from branches in the first layer towards those in the last layer. The effective power in each branch is held constant to the value obtained in the backward sweep during this step.

The backward sweep starts with branches in the last layer, moving towards the root node branches. Effective power flows in each branch are obtained by considering the node voltages of the previous iteration. The voltages obtained during the forward sweep are held constant during this step, and updated power flows in each branch are transmitted backward along the feeder using the backward path.

The forward and backward sweep method has three variants determined by the quantity calculated during each iteration's backward sweep. These include:

1. The current summation method, where the branch currents are evaluated.
2. The power summation method, where the power flow in the branches is evaluated.
3. The admittance summation method where, node by node, the driving point admittances are evaluated.

The advantage of this method is that the Jacobian Matrix is not required. Also, this method is suitable for radial and weakly meshed networks with a high R/X ratio. It also has a fast convergence (Madjissembaye et al., 2016). In general, the backward-forward sweep is carried out in the following steps as enumerated by (Sunisith & Meena, 2014). The backward-forward sweep is carried out iteratively until a convergence criterion is met. This criterion is set in the program such that if the solutions obtained in the subsequent iterations are consistently similar, the program stops execution.

2.3.2.1 Nodal Current Calculation

At iteration k , the nodal current injection $I_i^{(k)}$, at a network node i is calculated using equation (2.11).

$$I_i^{(k)} = \left(S_i / V_i^{(k-1)} \right)^* - Y_i V_i^{(k-1)} \quad i = 1, 2, \dots, n \quad (2.11)$$

where,

$V_i^{(k-1)}$ is the voltage at node i calculated during the $(k-1)^{th}$ iteration

S_i is power injection at node i

Y_i is the sum of all shunt elements at node i

2.3.2.2 Backward Sweep

At iteration k , starting from the branches in the last node and moving towards the branches connected to the root node, the current in the branch L is calculated by equation (2.12).

$$J_L(k) = -I_{i+1}(k) + \sum_1^n J_n \quad (2.12)$$

where, $J_L(k)$ is the current in branch L at iteration k , $I_{i+1}(k)$ is current injection at the node $i+1$, and $L = b, b-1, b-2, \dots, 1$. and b is the number of branches as shown in Figure 2.4.

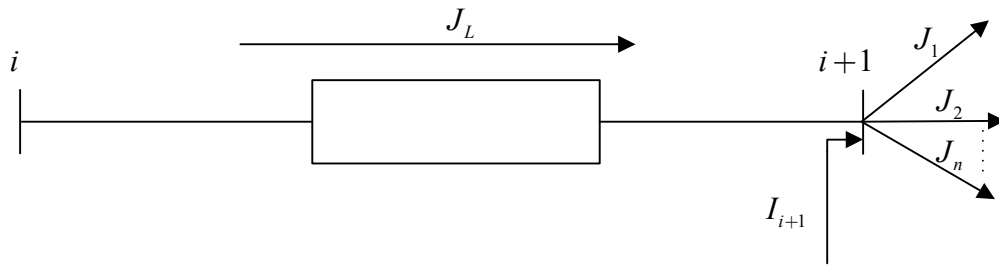


Figure 2.4: Relationship between branch and node current.

This is the direct application of Kirchhoff's Current Law.

2.3.2.3 Forward Sweep

Nodal voltages are updated in a forward sweep starting from branches in the first layer toward those in the last layer. For each branch L , the voltage at the node L_2 is calculated using the updated voltage at the node L_1 and the branch current calculated in the preceding backward sweep, as shown in equation (2.13).

$$V_{L2}(k) = V_{L1}(k) - Z_L J_L(k) \quad L = 1, 2, \dots, b \quad (2.13)$$

where, Z_L is the series impedance of branch L . b is the number of branches. This is the direct application of Kirchoff's Voltage Law.

2.3.2.4 Network Matrices

Network matrices are required in the backward-forward sweep. The necessary network matrices are the admittance matrix, Y for calculating nodal currents and a series impedance matrix Z to calculate nodal voltages. The bus admittance matrix can be obtained by determining the relation between the variables and parameters of the primitive network to bus quantities of the network using the bus incidence matrix. A primitive network is shown in Figure 2.5. Consider the impedance form shown in Figure 2.5(a) and let $V_p > V_q$. e_{pq} is the voltage source of self-impedance Z_{pq} , in series. The voltage equation can be written as:

$$\begin{aligned} V_p + e_{pq} - Z_{pq} i_{pq} &= V_q \\ \text{or} \\ V_{pq} + e_{pq} &= Z_{pq} i_{pq} \end{aligned} \quad (2.14)$$

where $V_{pq} = V_p - V_q$ is the voltage across P-Q and i_{pq} is current through P-Q.

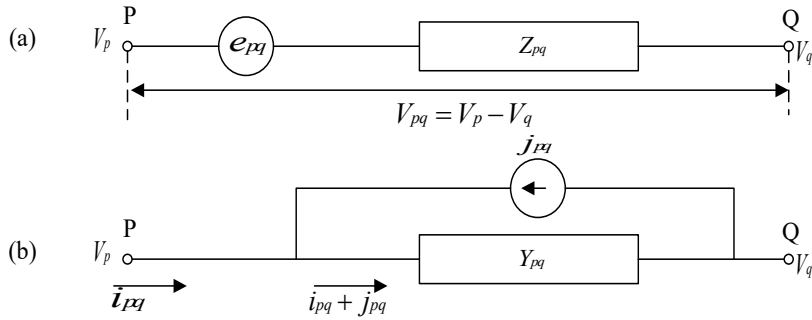


Figure 2.5: (a,b) primitive network, impedance, and admittance form.

Again consider the admittance form of the primitive network shown in Figure 2.5(b). The branch current equations can be written as:

$$\begin{aligned}
 i_{pq} + j_{pq} &= Y_{pq} V_{pq} \\
 \text{and} \\
 j_{pq} &= -Y_{pq} e_{pq}
 \end{aligned}
 \tag{2.15}$$

The primitive network's performance equations can be derived from equations (2.14) and (2.15). To describe the entire network, the variables become column vectors, and the parameters become matrices. The performance equations in impedance and admittance form therefore become:

$$\begin{aligned}
 \bar{\mathbf{V}} + \bar{\mathbf{e}} &= \bar{\mathbf{Z}}_p \bar{\mathbf{i}} \\
 \bar{\mathbf{i}} + \bar{\mathbf{j}} &= \bar{\mathbf{Y}}_p \bar{\mathbf{V}} \\
 \bar{\mathbf{Y}}_p &= \bar{\mathbf{Z}}_p^{-1}
 \end{aligned}
 \tag{2.16}$$

The diagonal elements are the impedances or admittances of the element p–q, and the off-diagonal elements are mutual impedances/admittances. The relationship between

the variables and parameters of a primitive network can be obtained from graph theory (El-Keib, 2002). The bus admittance matrix can be written as:

$$\bar{\mathbf{Y}}_B = \bar{\mathbf{A}}\bar{\mathbf{Y}}_p\bar{\mathbf{A}}^T \quad (2.17)$$

where, $\bar{\mathbf{A}}$ is the bus incidence matrix, $\bar{\mathbf{Y}}_p$ is the primitive admittance matrix, and $\bar{\mathbf{A}}^T$ is the transpose of the bus incidence matrix. The loop impedance matrix can be written similarly.

$$\mathbf{Z}_L = \bar{\mathbf{B}}\bar{\mathbf{Z}}_p\bar{\mathbf{B}}^T \quad (2.18)$$

where $\bar{\mathbf{B}}$ is the basic loop incidence matrix, $\bar{\mathbf{B}}^T$ its transpose, and $\bar{\mathbf{Z}}_p$ the primitive bus impedance matrix.

The incidence matrix $\bar{\mathbf{A}}$ has n rows that correspond to n nodes and e columns which correspond to e elements. The matrix elements can be formed as follows:

$a_{ij} = 1$, if the j th element is incident to and directed away from the node i .

$a_{ij} = -1$, if the j th element is incident to but directed towards from the node i .

$a_{ij} = 0$, if the j th element is not incident to the node i

Since the node currents have been calculated using equation (2.11), branch currents can be obtained using the bus incidence matrix using equation (2.19). This is done in the backward sweep procedure.

$$\bar{\mathbf{J}}_L = \bar{\mathbf{A}}^{-t}\bar{\mathbf{I}}_L \quad (2.19)$$

where, $\bar{\mathbf{A}}^{-t}$ is the transpose of the node incidence matrix and $\bar{\mathbf{I}}_L$ is the node current vector.

In the forward sweep, the branch voltage drops are calculated using equation (2.20) and used to calculate the change in the node voltages using equation (2.21).

$$\overline{\mathbf{V}}_L = \text{diag}(\overline{\mathbf{Z}}_L)\overline{\mathbf{J}}_L \quad (2.20)$$

where $\overline{\mathbf{V}}_L$ is the branch voltage drop vector, $\overline{\mathbf{Z}}_L$ is the loop impedance matrix, and $\overline{\mathbf{J}}_L$ is the branch current vector.

$$\overline{\Delta\mathbf{V}} = \overline{\mathbf{A}}^{-1}\overline{\mathbf{V}}_L \quad (2.21)$$

The updated bus voltages are calculated using equation (2.22), and the process is repeated until convergence.

$$\overline{\mathbf{V}}_{Ln} = \overline{\mathbf{V}}_0 - \overline{\Delta\mathbf{V}} \quad (2.22)$$

where $\overline{\mathbf{V}}_{Ln}$ is the updated node voltage vector and $\overline{\mathbf{V}}_0$ is the vector equal to initial values that are assumed to be one p.u.

2.3.3 Direct method (BIBC/BCBV matrix Method)

This method has been applied in (Mishra et al., 2016) to solve load flow for a radial distribution system. It uses three steps: equivalent current injection, the formulation of Branch injection to Branch Current (BIBC) matrix, and a Branch Current to Bus Voltage (BCBV) matrix. This method eliminates the formation of the Jacobian matrix, and therefore, its implementation is less time-consuming. It is effective for the analysis of radial networks.

2.3.4 Implicit Z_{BUS} Gauss Method

This method has been used in (Patil & Kurkani, 2014) to solve load flow for a three-phase unbalanced radial distribution network. This method works on the principle

of superposition. The voltage at each bus arises from the contribution of source bus voltage and the equivalent current injections. When using the superposition principle, only one type of source is considered at a time while determining the bus voltages. That means that when the slack bus is connected, all current injections are disconnected and vice versa. This method performs better in execution time and convergence rate than the conventional Newton Raphson method because it does not require computation of Jacobian elements.

2.3.5 Loop impedance method

The loop impedance matrix concept has been used in [26] to solve the power flow of the three-phase unbalanced radial distribution system. This method is based on graph theory, where basic loop incidence matrix \mathbf{C} and branch-path incidence matrix \mathbf{K} of a connected graph are used to describe the system. This method has a fast convergence for large unbalanced radial distribution networks. Also, it does not require the formation of an admittance matrix and therefore offers less computation time.

2.3.6 Newton Based Methods

Newton-based methods are modified forms of the conventional Newton Raphson power flow solution. The modification is necessary because of the unique characteristics of distribution networks, such as high R/X ratios, which affect the convergence of the conventional Newton Raphson power flow method. In (Sereeter et al., 2017), Polar Current Mismatch Version has been used to solve a three-phase power flow problem in the distribution network. This version is obtained using the current mismatch functions in polar co-ordinates.

Other versions include Cartesian current mismatch, complex current mismatch, Cartesian power mismatch, and complex power mismatch, which are detailed in (Sereeter et al., 2019). Newton Based Methods have the disadvantage of using the Jacobian Matrix, which increases the computation time, especially for large distribution networks.

2.4 Distributed Generation

This section defines distributed generation and various classifications of distributed generation in literature. Also, the section reviews the characteristics of distributed generation.

2.4.1 Definition, classification, and their characteristics

Distributed generation can be defined as an electric power source connected directly to the distribution network and located away from other sources feeding the distribution network (Ackermann et al., 2001). There are many types of DGs that vary from type and technologies used. In (El-Khattam & Salama, 2004), a comprehensive classification of DG technology has been given. The researchers classified DGs into two broad categories: traditional generators (combustion engines) and non-traditional generators. Traditional generators include microturbines such as natural gas turbines. Non-traditional generators include electrochemical devices (fuel cells), storage devices (batteries), and renewable devices such as photovoltaics (PV) and wind turbines.

DGs vary in size, and the primary energy characteristics largely determine their output characteristics. Based on their output characteristics, DGs are either dispatchable or non-dispatchable. The operator can control Dispatchable DGs to ensure the desired

voltage and power output is maintained at the DG bus. However, non-dispatchable DGs are difficult to control due to their output's intermittent nature caused by the primary energy source's unpredictability.

In addition to the above classification, DGs are also classified as Type 1, Type 2, Type 3, and Type 4 DGs (Hung et al., 2010). Type 1 DGs only deliver active power and include photovoltaics, fuel cells, and microturbines. Type 2 DGs deliver only reactive power. They include synchronous compensators such as gas turbines. Type 3 DGs deliver both active and reactive power. These DGs are based on synchronous machines. Type 4 DGs deliver active power while consuming reactive power. Induction Generators used in wind farms are in this category.

Voltage stability of distribution systems with DGs mainly depends on control strategies, capacity, and DGs location. Therefore, it is vital to know the mode of operation of the DGs during the planning stage so that the effect of their operation on voltage stability is known. DGs are usually operated in power factor control mode, where the power factor is kept constant (Hashim et al., 2012). In this mode, the reactive power follows the real power variation. This mode of operation can therefore allow the simultaneous placement of DGs, both dispatchable and non-dispatchable, and capacitors on the same bus with appropriate co-ordinated control of DG active power and reactive power output, and capacitor reactive power.

2.5 Optimization Methods applied to sizing and placing DGs and Static capacitors

This section reviews the optimization methods applied in DG and capacitor placement. A comprehensive review is given for the classification of optimization methods in sections 2.5.2, 2.5.3, and 2.5.4. Finally, heuristic methods used in this work have been reviewed in sections 2.5.4.1, 2.5.4.2, and 2.5.4.3.

2.5.1 Introduction

Power systems optimization is an important area in Power Systems Engineering because it contributes to saving costs, improved operational reliability, and system security. Power systems have grown to become large and complex. Therefore there is a need to develop optimization techniques that will deal with many inherent constraints in solving power systems optimization problems. This section reviews the various optimization techniques applied in power systems optimization, particularly DG and capacitor placing and sizing.

2.5.2 Analytical Methods

These are classical optimization methods that use classical mathematics theories such as calculus, algebra, and matrices to model physical systems and derive system variables' optimal values. In (Acharya et al., 2006), an analytical method based on the exact loss formula was used to calculate the optimal size of DG and identify the optimum location for DG placement to minimize total power loss in distribution systems. These researchers' analytical approach was based on placing a DG in one bus at a time and

calculating the network loss for each case until when the minimum loss is obtained. Therefore, their method cannot be used to place more than one DG in different locations simultaneously.

In (Jain et al., 2014), an analytical method based on two-port z-bus parameters was used to site and size DG for voltage stability enhancement. This work applied this analytical technique to site one DG in a 69-bus radial distribution network. Their method's efficiency has not been demonstrated in siting more than one DG in the network simultaneously. In (Gözel & Hocaoglu, 2009), an analytical technique based on loss sensitivity has been applied. The method uses the bus-injection to branch-current (*BIBC*) and branch-current to bus-voltage (*BCBV*) matrices to simplify the solution process. This method is only used for placing a single DG in the distribution network.

The loss sensitivity factor (LSF) was used in (Muthukumar & Jayalalitha, 2016) to place capacitors and distributed generators in radial distribution systems. This analytical method determines the sensor nodes that are more prone to loss reduction when active power and reactive power are injected by DG and shunt capacitor units at those buses. Another analytical method based on voltage stability index was applied in (Mohan. & Aravindhababu., 2010). In this method, a given threshold of stability index is set. All buses with an index less than the given threshold are provided with reactive compensation until all the buses have their indices greater than the given threshold. This analytical technique requires repeated calculations of voltage stability indices and reactive power values to

bring the stability indices to the set threshold. This analytical approach has also been used for comparison with the method used in this work.

2.5.3 Numerical Methods

Numerical methods involve computing numerical data in problems to produce a sequence approximation of data iteratively until obtaining the best solution. Numerical optimization methods include linear programming, ordinal optimization, non-linear programming, dynamic programming, and quadratic programming.

A linear programming method was used in (Keane & O'Malley, 2005) to solve the DG allocation problem. The objective function is to increase the generation capacity while ensuring that technical constraints are not breached. Dynamic programming has been used to solve the DG allocation optimization problem in (Khalessi & Haghifam, 2009) to enhance loss reduction and system reliability. Dynamic Programming decomposes the main problem into a series of single-stage decision problems, and optimization is done at each stage.

Dynamic programming does not guarantee an optimal solution because only a few potential solutions are saved during the search process. Mixed Integer Non-Linear Programming (MINLP) was applied in (Atwa et al., 2010) to solve the DG placement problem to minimize the annual system losses. The researchers used a probabilistic based planning approach to determine the optimal fuel mix of different types of DG units considering the uncertainties of renewable DG resources.

2.5.4 Heuristic Methods

Heuristic methods are computer-oriented approaches that use artificial intelligence to search for optimal solutions to an optimization problem. Artificial intelligence methods have a simple mathematical structure and simulate natural phenomena such as the behavior of living things. Search heuristics are particularly applicable when objective functions are highly nonlinear, and when the number of variables and constraints is large. Also, search heuristics reduce development time and are robust since they are insensitive to missing data (Kwang Y. Lee & El-Sharkawi, 2008). Researchers have applied heuristic methods in solving the DG and Capacitor optimization problem.

Kalman Filtering method was used in (Lee & Park, 2009) to solve the optimal placement problem of DGs for loss reduction. Kalman filter algorithm has smoothing properties and the ability to reject noise. This algorithm has been used to place multiple DGs, which effectively lead to system loss reduction. Since only a small sample of network data is used in the Kalman Filter Algorithm, the authors concluded that computational effort was reduced while at the same time reaching optimal solutions.

A particle swarm optimization algorithm has been used in (Antony & Baby, 2013) to solve the DG placement problem. Particle swarm optimization was also used in (Jamian et al., 2012) for multi DG problem for enhancing voltage stability. In (Mohamed Imran A & Kowsalya M, 2014), the Bacteria foraging optimization algorithm was used to find the optimal sizes of DGs and capacitors for power loss minimization. In (Mohapatra et al.,

2012), the Differential Evolution algorithm was used to optimize the placement of distributed generation and capacitors to minimize system losses.

In (Kasaei, 2014), Ant Colony Algorithm has been used to solve capacitor and DG placement problems for loss minimization and improvement of voltage stability problems in distribution systems. In (Khodabakhshian & Andishgar, 2016), intersect mutation differential evolution (IMDE) has been used to place DGs and Capacitors in radial distribution systems optimally. This method is a pure form of Evolution Programming Algorithm with no hybridization with other methods. Also, a Genetic Algorithm was used in (Moradi & Abedinie, 2010) to place DGs in IEEE-69 bus system. The GA method was used in its un-hybridized form. These un-hybridized methods have been used as a basis for comparison with the Hybrid Evolution Programming used in this work.

The section that follows gives a brief overview of the heuristic methods that have been applied in this work. The heuristic methods presented are Evolution Programming, Simulated Annealing, and Tabu search. The strengths of these methods have been outlined under each method.

2.5.4.1 Evolution Programming and its features

Evolution Programming (EP) is a computational optimization method in evolutionary computation, which uses natural evolution principles to find an optimal global solution to a given problem (Ongsakul & Dieu, 2016). As observed in (Kwang Y. Lee & El-Sharkawi, 2008), evolution programming is a useful optimization method when

other techniques such as gradient steepest descent or direct analytical discovery methods are not possible. The search space may contain many local optimum solutions.

Evolution Programming is a powerful and general global optimization tool. EP seeks the optimal solutions over several generations or iterations. Evolution Programming uses a mutation operator to generate a new population from an existing population. This technique is suitable for solving problems with real-valued function optimization. The general procedure of Evolution Programming is presented in Figure 2.6.

Evolution Programming operates on a population of individuals. Each individual represents a solution to the fitness function or the objective function. The algorithm often starts with a random initial population. The fitness of individuals in the initial population is evaluated, and the fittest individuals are selected using a suitable selection strategy. The chosen individuals form parents to the next population. The selected individuals undergo mutation to create offspring. The offspring and the parents make the new population, and the process of selection and mutation is repeated until there is convergence.

The basic operators of Evolution Programming are evaluation, mutation, and selection. Evaluation of individuals is done with the help of a fitness function, which is usually the objective function to be optimized. The fitness function guides the search process by calculating the fitness values, which are the input to the selection process. These values are used to determine the individuals that will appear in the future population.

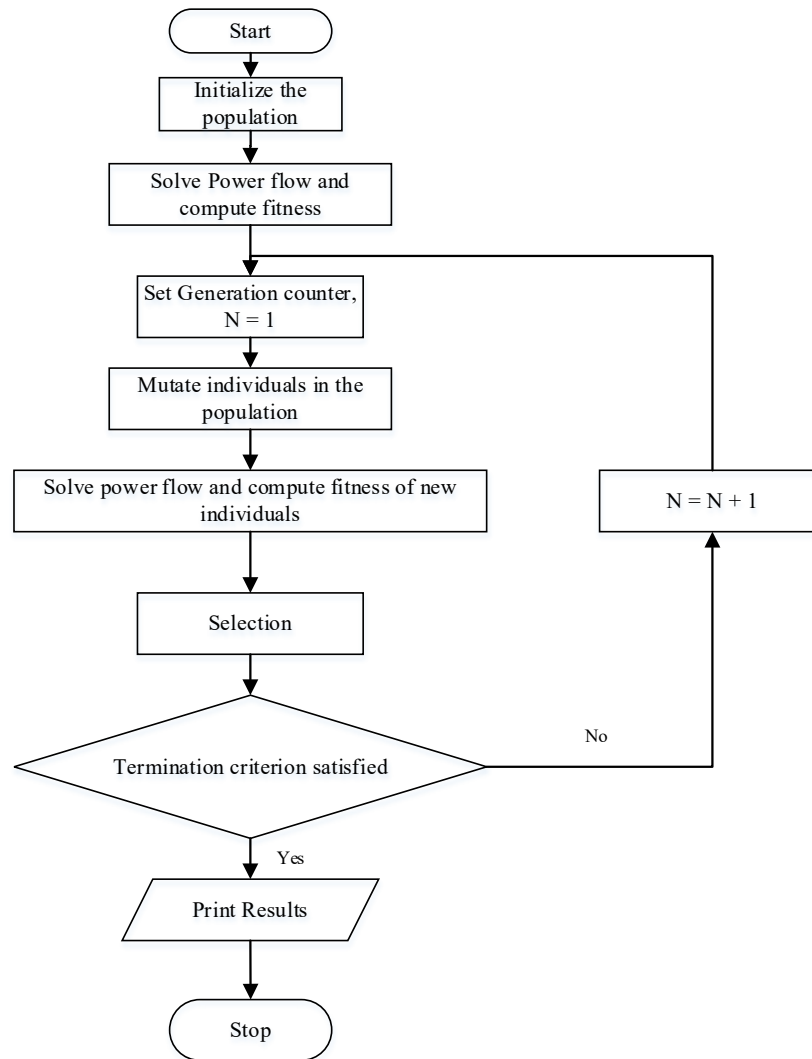


Figure 2.6: General Evolution Programming method.

Mutation is the random process of altering the information contained in an individual. The mutation operator works on individuals of the current population to form new offspring. There are two commonly used mutation operators, namely Gaussian operator and Cauchy operator. For a search problem that requires a real-valued vector that

minimizes a function $f(x)$, a vector of n dimensions, the evolution programming algorithm uses the Gaussian operator in equation (2.23) to generate new offspring.

$$x'_i = x_i + \sigma_i N(0,1) \quad (2.23)$$

where,

x'_i is the i th offspring

x_i is the i th parent

σ_i is the standard deviation of a Gaussian random variable denoted by $N(0,1)$

The mutation step size is done using two steps (Kwang Y. Lee & El-Sharkawi, 2008), as shown in equation (2.24) and equation (2.25).

$$\sigma'_i = \sigma_i \exp(\tau N_i(0,1) + \tau' N_i(0,1)) \quad (2.24)$$

$$x'_i = x_i + \sigma'_i N_i(0,1) \quad (2.25)$$

where τ and τ' are set by equations (2.26) and (2.27) as given in (Koenig, 2002),

$$\tau = \left(\sqrt{2\sqrt{n}} \right)^{-1} \quad (2.26)$$

$$\tau' = \left(\sqrt{2n} \right)^{-1} \quad (2.27)$$

The Cauchy mutation operator uses the Cauchy random variable to mutate individuals of a population using equation (2.28).

$$x'_i = x_i + \sigma'_i \delta \quad (2.28)$$

where δ is a Cauchy random variable with a distribution defined by equation (2.29).

$$\delta = \frac{1}{2} + \frac{1}{\pi} \arctan\left(\frac{x}{t}\right) \quad (2.29)$$

where t is a scale parameter.

The Cauchy density function is given by equation (2.30).

$$f(x) = \frac{1}{\pi} \left(\frac{t}{t^2 + x^2} \right), -\infty < x < \infty \quad (2.30)$$

The common mutation operator has the parameter $t = 1$ and is denoted as $C(0,1)$. When using the Cauchy mutation operator, equation (2.25) becomes equation (2.31).

$$x'_i = x_i + \sigma'_i C_i(0,1) \quad (2.31)$$

For Evolution programming to select individuals for the next population, the parents and offspring are combined. The combined population individuals compete with randomly selected individuals in the combined population for a chance to get selected (Lai, 1998). According to the competition, a weight value is assigned to an individual, as shown in equation (2.32).

$$w_i = \sum_{t=1}^N w_t \quad (2.32)$$

where, N is the population size, w_t is a number of $\{0,1\}$ which represents win 1 or loss 0 as p_i competes with a randomly selected individual p_r in the combined population. w_i is given by equation (2.33).

$$w_i = \begin{cases} 1 & f_i > f_r \\ 0 & \text{otherwise} \end{cases} \quad (2.33)$$

where, f_r is the fitness of a randomly selected individual p_r and f_i is the fitness of p_i . When all the individuals $p_i, i = 1, 2, \dots, 2N$ get their competition weights, they are ranked in descending order of their corresponding w_i . The first N individuals are selected to be members of the next population, together with corresponding fitness values f_i .

Researchers have applied EP to solve several power systems engineering problems. In (Lai, 1998), EP has been used to solve long term transmission network planning, estimating the transient and sub-transient parameters of a generator under normal operation, solving economic dispatch problem of units with non-smooth input-output characteristic functions, and also solving the optimal power flow problem in FACTS. Fuchs and Masoum (Fuchs & Masoum, 2008) concluded that EP is robust in searching for the real values of parameters even when the data is highly contaminated by noise as opposed to conventional methods such as analytical methods.

2.5.4.2 Simulated Annealing and its features

Simulated Annealing (SA) is a technique for solving hard combinatorial problems that emulates the physical process of annealing. SA was initially proposed in statistical mechanics to model the natural process of solidifying and forming the crystal (Kwang Y. Lee & El-Sharkawi, 2008). SA is used to optimize functions that are non-linear and have

many constraints. The two main features of SA are the cooling schedule and mechanism to transit between states.

The analogy between the annealing process and the optimization problem is presented as transitioning from an equilibrium state to another and reaching the minimum energy level. The optimization problem solutions are equivalent to the states of the physical system. The objective function's value is equivalent to a state's energy, and a control parameter is equivalent to the temperature in the annealing process (Soliman & Mantawy, 2012). A general simulated annealing algorithm is presented in Figure 2.7.

The control parameter of simulated annealing is the temperature, which is used to evaluate the probability of an uphill move. This probability is calculated using the Boltzmann's probability function given by equation (2.34).

$$P = \exp(-\Delta E / kT) \quad (2.34)$$

where,

ΔE is increase in Energy from one state to another

k is the Boltzmanns constant

T is the control Parameter which is Temperature

The control variable, T , is used to move the system from one state to the other, thereby exploring the search space. In the process of this movement, the states of minimum energy are realized. To lower the value of temperature, annealing schedules are used. In the annealing process, the temperature is raised so that the system melts. The temperature is lowered by a constant factor α taking enough steps at each temperature to

keep the system close to equilibrium until the system reaches the ground state, the minimum energy state (Nourani & Andresen, 1998)

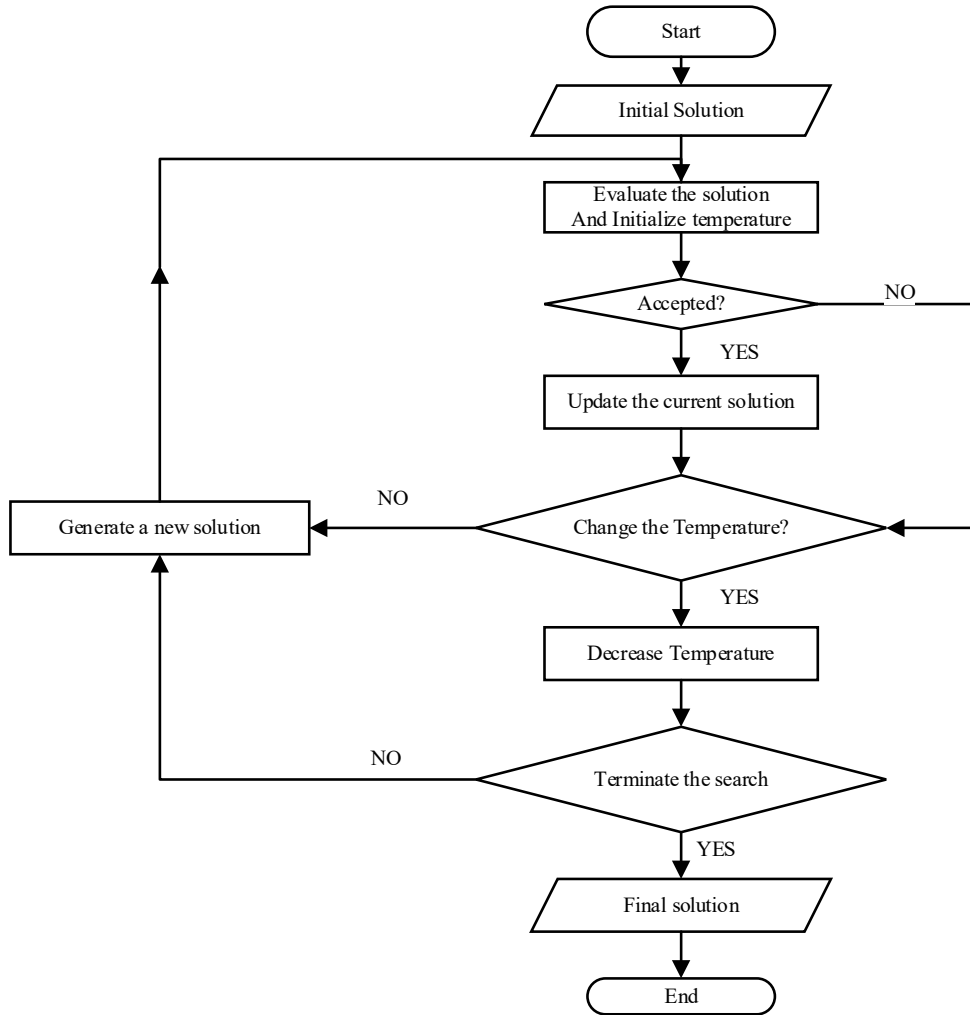


Figure 2.7: General simulated annealing algorithm.

The cooling schedule is mathematically represented in equation (2.35).

$$T(t) = T_0 \alpha^t \quad (2.35)$$

where,

T is Temperature

T_0 is initial temperature

α is constant factor between 0 and 1

t is time

The Acceptance criterion of a new solution can be given as a probability function arising from the Boltzmann function, as shown in equation (2.36).

$$A_{ij}(T) = \frac{1}{1 + \exp(-\Delta E / T)} \quad (2.36)$$

where,

$A_{ij}(T)$ is the probability of accepting a new solution based on control parameter T

ΔE is change of energy from one state to another

T is temperature (control) parameter

Simulated Annealing Algorithm is effective in network reconfiguration problem for large scale distributed systems, and its search capability is significant for large system sizes (Soliman & Mantawy, 2012). SA algorithm has been used in (Sutthibun & Bhasaputra, 2010) to solve multi-objective optimal placement of distributed generation. It was demonstrated that the resulting solution was able to reduce network power loss, emission, and system contingency compared to a system without DGs.

2.5.4.3 Tabu Search and its Features

Tabu search (TS) is a metaheuristic search method used to manage heuristic algorithms that perform local search (Kwang Y. Lee & El-Sharkawi, 2008). TS has strategies that provide a means of avoiding being trapped in local optimal solutions during the search space exploration process. Tabu Search is an iterative improvement procedure

that starts from an initial feasible solution and attempts to determine a better solution using the gradient descent algorithm (Soliman & Mantawy, 2012).

Tabu Search uses a memory element whereby it avoids revisiting some areas that have already been explored. These areas are referred to as Tabu and are forbidden. By avoiding these areas, new areas of the search space are investigated to avoid local minima and ultimately achieve global optimum. Tabu search preserves recent moves or iterations in memories called Tabu List. Together with the Aspiration Level associated with them, these memories are the Tabu Search Algorithm's main components.

A Tabu List is made by recording moves in which they are made whereby if a new element is added at the bottom, the oldest element at the top is dropped from the list. The aspiration level is the value for the evaluation function associated with each entry in the Tabu List. The aspiration criterion is used to override status if a move is considered good enough.

Figure 2.8 shows the general Tabu Search Algorithm, as presented in (Soliman & Mantawy, 2012). Tabu Search has been used to solve many optimization problems. In (Soliman & Mantawy, 2012), the TS algorithm has been used to solve the unit commitment problem. In (Pereira et al., 2016), a hybrid algorithm based on GA and TS was used to solve the optimal allocation of DGs and Reactive Power to minimize the investment and operational cost.

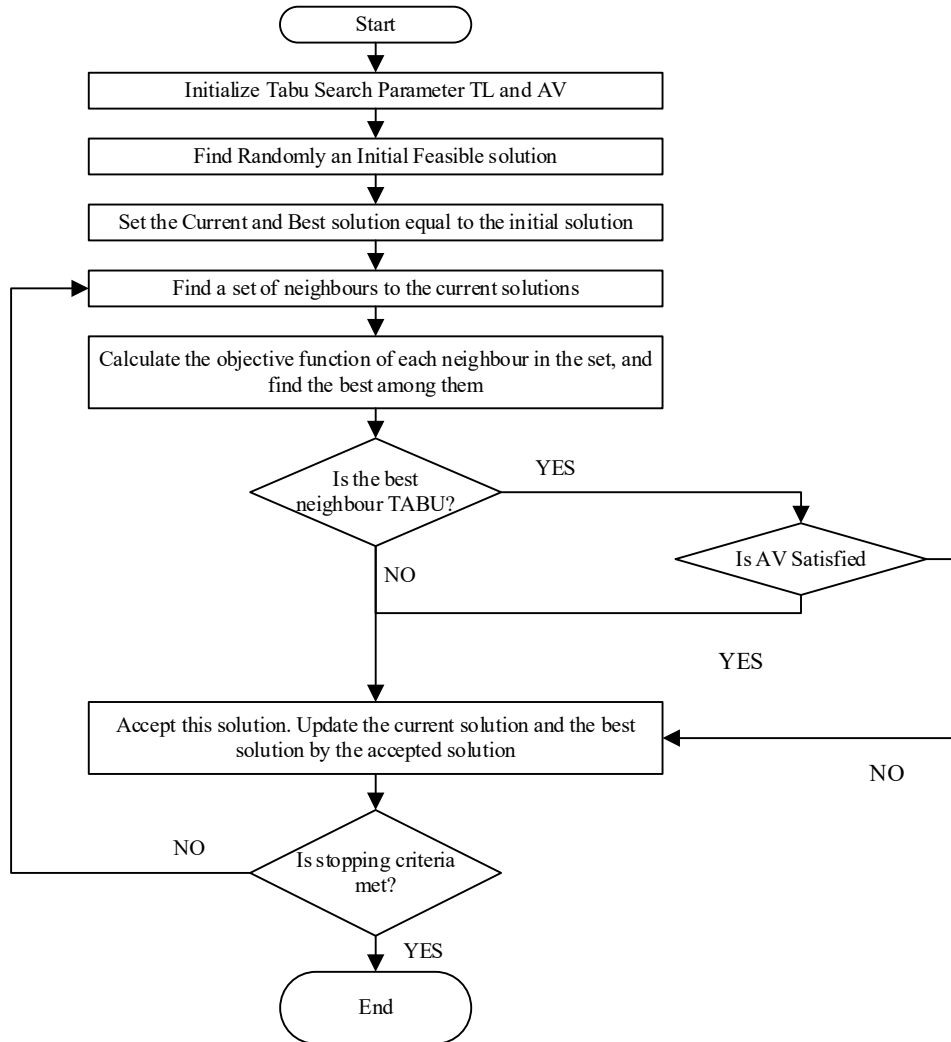


Figure 2.8: General Tabu Search Algorithm for solving an optimization problem.

2.6 The IEEE-33 Bus and IEEE-69 Bus radial distribution system modeling

The single line diagram of the reduced IEEE 33-bus distribution system is shown in Figure A.1. The system voltage is 12.66 kV, and the total system active and reactive loads are 3845 kW and 2305 kVAr, respectively. This test system consists of 33 buses and 32 branches. The bus data and branch data is shown in Table A-1 (Rajaram et al., 2015).

The IEEE 69-bus distribution system with 11-kV base voltage is shown in Figure A.2. It consists of one slack bus and 68 load buses. The total real and reactive power demand is 3801.890 kW and 2682.400 kVAR, respectively. This test system consists of 69 buses and 68 branches. The bus and branch data for the IEEE 69-bus is shown in Table A-2 (Savier & Das, 2007).

2.7 Summary and Research Gaps

This section has reviewed voltage stability and methods of its determination, power flow methods in radial distribution systems, distributed generation characteristics, optimization methods, and objective functions applied to sizing and placing DGs and static capacitors.

In the review of voltage stability, it has been established that researchers have developed voltage stability indices that measure how far or near a system is from voltage collapse. Voltage stability indices have become common, especially for analysis of large and complex networks, since they do not require rigorous analysis as opposed to traditional methods such as P-V and Q-V curve analysis methods. Therefore, this work uses the voltage stability index method to study voltage stability because of its simplicity and strengths when dealing with radial distribution systems.

The review of power flow methods used to analyze distribution systems revealed that Newton Based methods use the Jacobian matrix, which requires modification to adapt it to a distribution system's unique characteristics, including high R/X ratio and unbalanced loads. Methods that are not based on Newton, such as the Forward and

Backward Sweep method, BIBC/BCBV matrix method, Implicit Z_{BUS} Gauss Method, and Loop impedance method, exploit the topological structure of the distribution system. These methods reduce the number of equations and hence the computational burden. Therefore, it can be concluded that in solving load flow in distribution systems, methods that exploit the topological structure of the distribution system are more suited than the conventional methods such as Newton Raphson. Because of this, the Forward and Backward sweep method has been used in this work.

Distribution Generation technologies were also reviewed. In the review of DGs, it was observed that increased proliferation of DGs in distribution networks results in several adverse effects, including voltage variations, degraded protection, and altered transient stability. Voltage variation has been considered as the most dominant effect of distributed generation (Xu & Taylor, 2008). It was noted that the voltage stability of distribution systems with DGs mainly depends on control strategies, size, and location of the DGs. Therefore, it is vital for the network planner to optimally size and locate DGs and other network devices such as capacitors in the distribution network to alleviate voltage instability.

To optimally place and size DGs and static capacitors within distribution systems, optimization methods are used. Different optimization methods were reviewed. The methods reviewed were categorized into three categories: analytical methods, numerical methods, and heuristic methods. Analytical methods were observed not to be effective when dealing with multiple DG placement. They are, however, effective for single DG

placement. Numerical methods, on the other hand, were observed not to be accurate when solving ill-conditioned equations. This is because round-off errors in the solution process introduce small changes into the coefficient matrix, which introduces large errors to the final solution (Kiusalaas, 2005).

Heuristic methods were observed to have a simple mathematical structure and simulate natural phenomena such as animals' behavior. Heuristic methods were observed to be particularly applicable when objective functions are highly non-linear and when the number of variables and constraints is large. Heuristic methods also reduce development time and are also insensitive to missing data. In (Daud et al., 2016), a comprehensive review of methods of optimization in DG planning was done. The researchers reviewed numerical, analytical, and heuristic techniques and compared them as shown in Table 2-1.

From this comparison, it was observed that heuristic methods are the most suitable when dealing with large and complex optimization problems such as DG and Capacitor placement. In (Georgilakis & Hatziargyriou, 2013), a comprehensive review of methods used in DG placement was done. The researchers noted that heuristic methods are most efficient and provide robust and near-optimal solutions for large optimization problems. They also recommended improving heuristic algorithms' parameters to improve the efficiency and quality of solutions from these algorithms.

Table 2-1: A comparison of optimization methods.

	Method		
	Heuristic	Numerical	Analytical
Advantages	<ul style="list-style-type: none"> • Simple, flexible, and suitable for solving problems with large search space • It does not require conversion of the power system model into an optimization programming model • can search for a near-optimal solution 	<p>Accurate optimal solution</p>	<ul style="list-style-type: none"> • No convergence problem • Non-iterative • Simple
Disadvantages	<ul style="list-style-type: none"> • some of the algorithms get trapped in local optima hence resulting in sub-optimal solutions • slow convergence 	<ul style="list-style-type: none"> • Requires conversion of power system equations to an optimization model, a process that is difficult to manage 	<ul style="list-style-type: none"> • Difficult to apply when dealing with large and complex optimization problems such as DG placement in distribution networks • It does not guarantee an accurate solution

Hybridizing heuristic methods are instrumental in eradicating the problem of getting trapped in local optima, hence improving individual heuristic method performance. Therefore, this research uses a hybrid technique that incorporates Evolution Programming, Simulated annealing, and Tabu search in the DG and capacitor placement problem to enhance voltage stability in radial distribution networks.

CHAPTER THREE

METHODOLOGY

3.1 Outline of research stages

The objectives of this work were achieved, as shown in Figure 3.1.

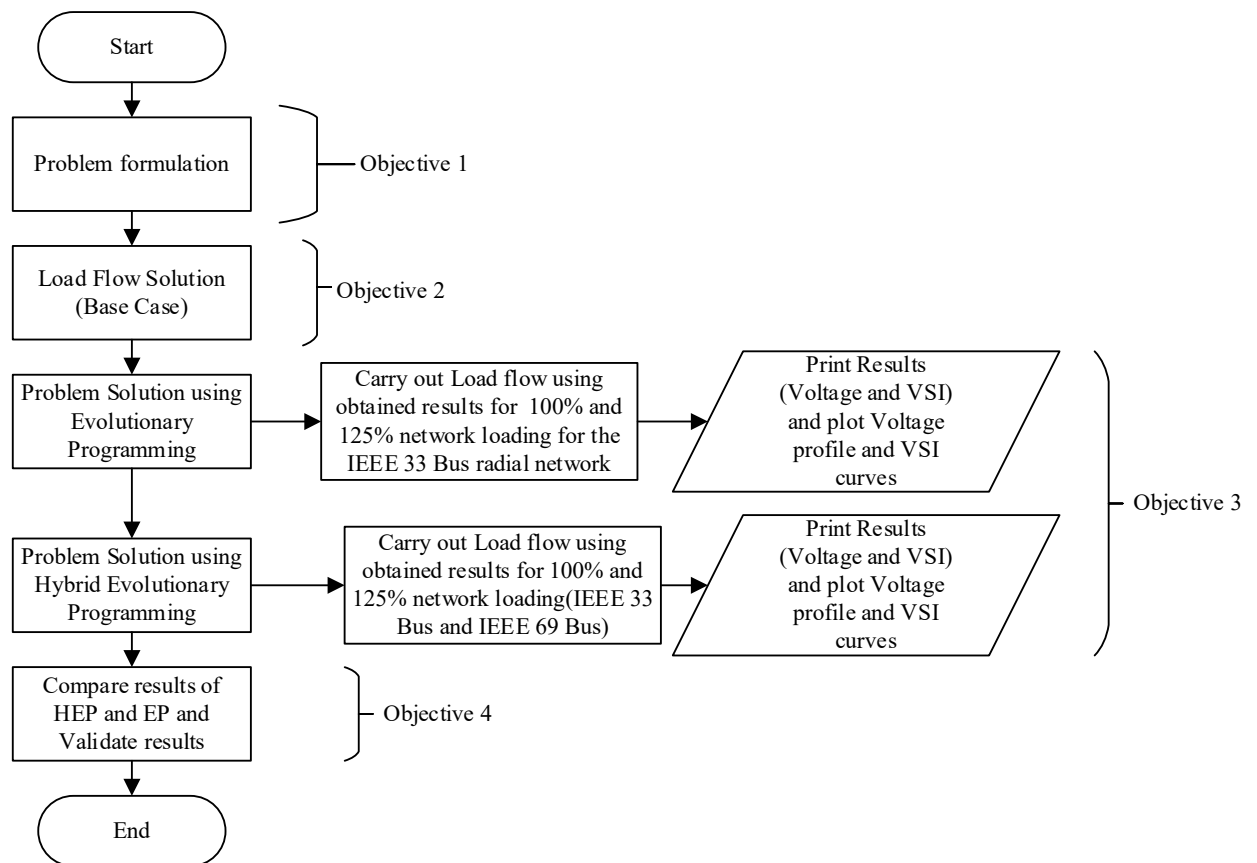


Figure 3.1: Flow chart outlining the research stages.

The placement problem was formulated based on the Voltage Stability Index presented (Chakravorty & Das, 2001). The closer VSI value is to zero, the more prone the bus is to voltage instability. A zero value for VSI represents voltage collapse. Therefore,

the VSI value should be as far as possible from zero. A load flow was done using the Forward-backward sweep load flow method. Voltage stability indices at all buses were determined.

These stability indices were ranked from the smallest to the largest. The maximum DGs and Capacitor locations were determined by dividing the maximum DG penetration by the maximum DG size allowable. This number was used to determine the number of buses corresponding to the lowest-ranked indices, which were taken as candidates for DG and Capacitor placement.

The DGs were taken to operate in PQ mode with a power factor of unity. They, therefore, produce only active power at the buses they are installed. Reactive power is provided by the capacitors, simultaneously placed at the candidate buses together with the DGs. To limit the capacitor's maximum size, the power factor resulting from both DG and capacitor placement was taken as 0.9. Synchronous generators usually operate at a power factor of 0.85. The power factor can be improved at the expense of reducing the active power.

However, shunt capacitors are usually installed at the generator bus to improve the power factor. An optimal power factor is crucial to minimize the power loss of a distribution system. Optimal power factor of the generator and capacitor are selected to match the power factor of the load (Hung et al., 2010). Utilities require that the load power factor be a minimum of 0.9 so that the losses are minimized. Therefore, a power factor of 0.9 at the bus where the DG is installed is appropriate to set the capacitor maximum limit.

Once the location for placement was identified, the next task is to identify the optimal size of the DGs and capacitors that would improve the voltage stability indices of the candidate buses without violating the system constraints. Evolution Programming was used to search for the optimal sizes that maximize the voltage to identify the optimal size in a radial distribution network. The radial network used was the IEEE 33 bus. This radial network is the most common used test radial network for testing algorithms. The size results of DGs and capacitors obtained were used to carry out load flow for the IEEE 33-bus radial network with 100% and 125% network loading. Since load growth is expected for distribution systems, 25% is allowed to analyze the distribution system's voltage stability with this growth. Plots for VSI and voltage profile were made.

This procedure was repeated using the developed Hybrid Evolution Programming, and the results obtained were compared with those of Evolution Programming to test the performance of this method. The Hybrid Evolution Programming was also used to place the DGs and capacitors in the IEEE-69 bus radial network, which is a larger radial network, to test the applicability of the HEP method on a larger network.

3.2 Detailed Plan

This section details the stages followed in this research. Problem formulation has been detailed in section 3.2.1. Sizing using Evolution Programming has been detailed in section 3.3, and sizing using Hybrid Evolution Programming has been detailed in section 3.4.

3.2.1 Problem Formulation

The placement problem's objective function was based on the Voltage Stability Index presented in (Chakravorty & Das, 2001). The aim was to place DGs and capacitors in the radial distribution system to enhance voltage stability. The function to be maximized was:

$$f(VSI) = \sum_{i=2}^n VSI_i \quad (3.1)$$

where,

$$VSI_i = |V_s|^4 - 4V_s^2(R_i P_{Li} + X_i Q_{Li}) - 4(X_i P_{Li} - R_i Q_{Li})^2 \quad (3.2)$$

and

$i = 2, 3, 4, \dots, n$, representing the total number of buses

V_s is the source voltage

Q_{Li} is the total reactive power fed through node i

P_{Li} is the total active power fed through node i

R_i is the resistance between source bus and node i

X_i is the reactance between source bus and node i

Equation (3.1) was maximized subject to the following load flow equations and operational constraints.

3.2.1.1 Equality constraints

The equality constraints include non-linear recursive power flow equations formulated as follows:

$$P_{i+1} = \left[P_{i,i+1} - \left(R_{i,i+1} \frac{P_{i,i+1}^2 + Q_{i,i+1}^2}{|V_i|^2} \right) - P_{i+1}^L + \alpha_{P_{DG}} P_{i+1}^{DG} \right] \quad (3.3)$$

$$Q_{i+1} = \left[Q_{i,i+1} - \left(X_{i,i+1} \frac{P_{i,i+1}^2 + Q_{i,i+1}^2}{|V_i|^2} \right) - Q_{i+1}^L + \alpha_{Q_{QC}} Q_{i+1}^C \right] \quad (3.4)$$

and

$$|V_{i+1}|^2 = |V_i|^2 - 2(P_{i,i+1}R_{i,i+1} + Q_{i,i+1}X_{i,i+1}) + (P_{i,i+1}^2 + Q_{i,i+1}^2) \left(\frac{R_{i+1}^2 + X_{i+1}^2}{|V_i|^2} \right) \quad (3.5)$$

where,

$i = 1, 2, 3, \dots, n$, representing the total number of buses.

P_{i+1} is active power through node $i + 1$

Q_{i+1} is reactive power through node $i + 1$

$|V_i|$ is the voltage magnitude at node i

$P_{i,i+1}$ is active power flow in the branch between node i and $i + 1$

$Q_{i,i+1}$ is reactive power flow in the branch between node i and $i + 1$

$X_{i,i+1}$ the reactance of branch between node i and $i + 1$

$R_{i,i+1}$ the resistance of branch between node i and $i + 1$

$\alpha_{P_{DG}}$ is the DG active power multiplier set to 1 where there is a DG and 0 where there is none

P_{i+1}^L is the active power load at node $i+1$

Q_{i+1}^L is the reactive power load at node $i+1$

$\alpha_{Q_{QC}}$ is the reactive power multiplier set to 1 where there is a capacitor and 0 where there is none

Q_{i+1}^C is the capacitor reactive power load at node .

3.2.1.2 Inequality Constraints

The inequality constraints include:

- a) The operational voltage limits were set using equation (3.6).

$$V_{i \min} \leq V_i \leq V_{i \max} \quad (3.6)$$

- b) The thermal capacity limits were set using equation (3.7).

$$|I_{i,i+1}| \leq |I_{i,i+1}|_{\max} \quad (3.7)$$

- c) Static stability of a distribution system is only improved when the DG penetration level η is below 50% (Hu et al., 2015). Therefore, equation (3.8) is used to limit the penetration level.

$$\frac{\sum_{i=1}^n P_{i+1}^{DG}}{P_{Load}} \leq \eta \quad (3.8)$$

d) The DG active power limits were set using equation (3.9).

$$0 \leq P_i^{DG} \leq P_{DG \max} \quad (3.9)$$

e) The capacitor reactive power limits were set using equation (3.10).

$$0 \leq Q_i^C \leq Q_{C \max} \quad (3.10)$$

The total number of buses for DG placement was determined using equation (3.11).

$$\text{No. of Locations} = \frac{\text{maximum DG penetration}}{\text{maximum DG size}} \quad (3.11)$$

Table 3-1 shows the parameters for the optimization problem. The inequality constraints were enforced using the penalty function shown in equation (3.12)

$$PF = k \left(\sum_{i=1}^n h(V_i) + \sum_{i=1}^n h(P_i^{DG}) + \sum_{i=1}^n h(Q_i^C) + \sum_{i=0}^{n-1} h(|I_{i,i+1}|) \right) \quad (3.12)$$

where,

PF is the penalty function.

k is the penalty coefficient

$$h(x) = \begin{cases} (x - x^{\max})^2 & \text{if } x > x^{\max} \\ (x^{\min} - x)^2 & \text{if } x < x^{\min} \\ 0 & \text{if } x^{\min} \leq x \leq x^{\max} \end{cases} \quad (3.13)$$

x^{\min} is the lower limit of the variable x

x^{\max} is the upper limit of the variable x

The penalty coefficient is usually taken as values between 10^3 and 10^6 (Ongsakul & Dieu, 2016).

The objective function, therefore, becomes equation (3.14):

$$f(VSI) = \sum_{i=2}^n VSI_i + PF \quad (3.14)$$

Table 3-1: Optimization problem parameters.

Parameter	Value
Maximum DG penetration, η (Hu et al., 2015)	50%
Maximum DG Size	500kW
Maximum voltage at a bus $ V_i _{\max}$	1.05p.u
Minimum voltage at a bus $ V_i _{\min}$	0.95p.u
Total network active power demand (IEEE-33 Bus)(Rajaram et al., 2015)	3.715MW
Maximum DG penetration in kW (IEEE-33 Bus)	1857.5kW
No. of locations=Max. DG penetration/max. DG size (IEEE-33 Bus)	4
Total network active power demand (IEEE-69 Bus)(Savier & Das, 2007)	3.792MW
Maximum DG penetration in kW (IEEE-69 Bus)	1895.945kW
No. of locations=Max. DG penetration/max. DG size (IEEE-69 Bus)	4

3.2.2 Load Flow Analysis

To calculate the initial network parameters, a load flow was done. The load flow technique used was the backward/forward sweep load flow method. The voltage stability indices (VSI) for the network were calculated in addition to the load flow. A ranking is done to determine the locations with the lowest VSI that would be candidates for installing DGs and capacitors. The load flow results and corresponding VSI are shown in Table 3-2 and Table 3-3.

Table 3-2: Load flow data and VSI for IEEE-33 Bus Network.

Bus No.	Vbus	VSI	Rank	Bus No.	Vbus	VSI	Rank
1	1	1	33	18	0.9036	0.669	1
2	0.997	0.9993	32	19	0.9965	0.938	27
3	0.983	0.9846	30	20	0.9929	0.986	31
4	0.975	0.9314	26	21	0.9922	0.972	29
5	0.968	0.9033	23	22	0.9915	0.969	28
6	0.949	0.8739	21	23	0.9792	0.915	24
7	0.946	0.8119	19	24	0.9725	0.919	25
8	0.932	0.7987	17	25	0.9692	0.894	22
9	0.926	0.7545	14	26	0.9474	0.817	20
10	0.92	0.7343	13	27	0.9448	0.805	18
11	0.919	0.7161	10	28	0.9334	0.796	16
12	0.918	0.7134	9	29	0.9251	0.759	15
13	0.911	0.7085	8	30	0.9216	0.732	12
14	0.909	0.6898	5	31	0.9174	0.721	11
15	0.908	0.6829	4	32	0.9164	0.708	7
16	0.906	0.6787	3	33	0.9161	0.705	6
17	0.904	0.6746	2				

Table 3-3: Load flow data and VSI for IEEE-69 Bus Network.

Bus No.	Vbus	VSI	Rank	Bus No.	Vbus	VSI	Rank
1	1.0000	1.0000	69	36	1.0000	0.9960	55
2	1.0000	1.0000	66	37	1.0000	1.0000	60
3	1.0000	1.0000	66	38	0.9990	1.0000	61
4	1.0000	1.0000	62	39	0.9990	0.9960	54
5	0.9990	1.0000	58	40	0.9990	0.9960	56
6	0.9860	0.9951	50	41	0.9980	0.9960	51
7	0.9740	0.9443	40	42	0.9980	0.9920	44
8	0.9710	0.8999	39	43	0.9980	0.9920	47
9	0.9690	0.8889	37	44	0.9980	0.9920	48
10	0.9630	0.8814	35	45	0.9980	0.9920	45
11	0.9610	0.8600	33	46	0.9980	0.9920	49
12	0.9570	0.8528	30	47	1.0000	0.9920	46
13	0.9530	0.8387	28	48	0.9980	1.0000	57
14	0.9490	0.8248	25	49	0.9930	0.9918	43
15	0.9450	0.8110	24	50	0.9920	0.9723	42
16	0.9440	0.7975	22	51	0.9710	0.9684	41
17	0.9430	0.7941	21	52	0.9710	0.8889	38
18	0.9430	0.7908	20	53	0.9650	0.8889	36
19	0.9430	0.7908	18	54	0.9610	0.8671	34
20	0.9420	0.7908	19	55	0.9550	0.8527	29
21	0.9420	0.7874	15	56	0.9490	0.8316	26
22	0.9420	0.7874	17	57	0.9180	0.8061	23
23	0.9410	0.7874	16	58	0.9030	0.7091	9
24	0.9410	0.7841	11	59	0.8970	0.6647	8
25	0.9410	0.7841	10	60	0.8900	0.6472	7
26	0.9410	0.7841	12	61	0.8800	0.6270	6
27	0.9410	0.7841	13	62	0.8790	0.5997	4
28	1.0000	0.7841	14	63	0.8790	0.5970	3
29	1.0000	1.0000	65	64	0.8760	0.5969	2
30	1.0000	1.0000	63	65	0.8750	0.5889	1
31	1.0000	1.0000	68	66	0.9610	0.6001	5
32	1.0000	1.0000	64	67	0.9610	0.8529	32
33	0.9990	1.0000	59	68	0.9560	0.8529	31
34	0.9990	0.9960	52	69	0.9560	0.8353	27
35	0.9990	0.9960	53				

From Table 3-2, the buses that formed candidates for installation of DG and capacitor are 18, 17, 16, and 15 owing to their low VSIs. The candidate buses for DG and Capacitor installation for the IEEE-69 Bus network were bus 65, 64, 63, and 62.

3.3 Sizing using Evolution Programming

After identifying the location for the installation of DGs and capacitors, the Evolution Programming method was used to obtain the optimal sizes. The procedure is as shown in Figure 3.2.

The algorithm is explained in the following steps.

1. Representation of solution

Each trial solution was represented by the vector $S_p^T = [P_{Li} \quad Q_{Li}]$, where P_{Li} and Q_{Li} is the total active and reactive power, respectively, fed through the node i .

2. Initialization

The values of V_s , R_{si} and X_{si} of equation (3.2) are constants. V_s is set to 1, whereas values of R_{si} and X_{si} were calculated in per unit.

The initial population was initialized randomly using a random uniform number and limiting the value of each element of the individual to be between the upper and lower boundaries of each variable, as shown in equation (3.15).

$$x_i = x_i^{\min} + u(x_i^{\max} - x_i^{\min}) \quad (3.15)$$

where,

x_i is the i th element of an individual in the population

x_i^{\min} is the lower limit of the i th element of the individual in the population

x_i^{\max} is the upper limit of the i th element of the individual in the population

u is a random uniform number in the interval $[0,1]$

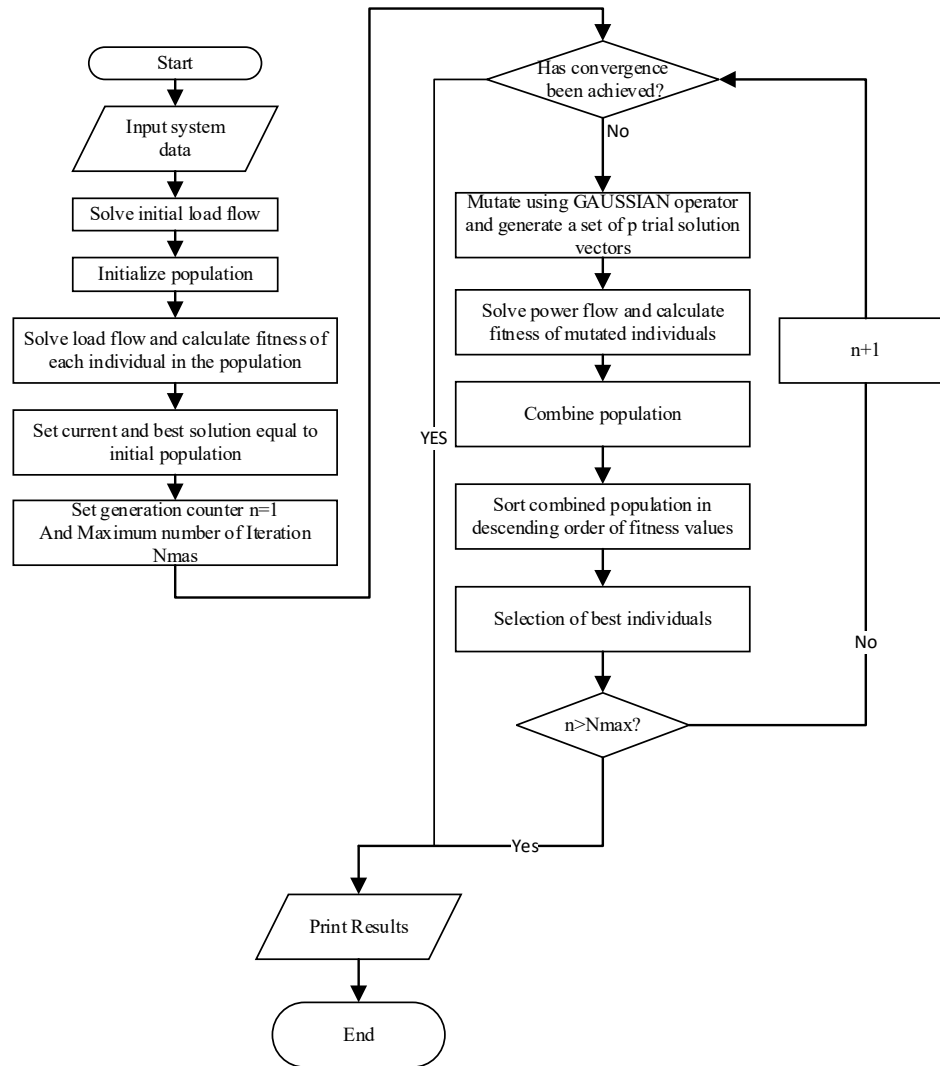


Figure 3.2: Evolution Programming Algorithm used to find DGs and Capacitors sizes.

3. Power Flow solution

Power flow was run to determine the values of injected active and reactive power at each bus. Also, the voltage at each bus was determined.

4. Fitness Calculation

The fitness was calculated from the objective function shown in equation (3.14) to determine the optimality of the candidate solution.

5. Mutation

Gaussian mutation operator was used to generate individuals of a new population.

This was done using equation (3.16).

$$x'_{m,i} = x_{m,i} + N(0, \sigma_{m,i}^2) \quad (3.16)$$

$$\sigma_{k,i} = (x_i^{\max} - x_i^{\min}) \left(\frac{f_{\max} - f_m}{f_{\max}} \right) \quad (3.17)$$

where,

$x'_{m,i}$ is the value of the i th element of the k th offspring individual

$x_{m,i}$ is the value of the i th element of the k th parent individual

$N(0, \sigma_{m,i}^2)$ is the Gaussian Random number with a mean of zero and a standard deviation of $\sigma_{m,i}$

x_i^{\min} is the lower limit of the i th element of the individual in the population

x_i^{\max} is the upper limit of the i th element of the individual in the population

f_{\max} is the maximum fitness of the parent population

f_m is the fitness value of the mth individual.

6. Selection

After the evolution of the population, a set of new offspring and parents was formed. To select a new population from the combined population set, a tournament scheme was used to select a new parent population for the next generation. This scheme is as shown in equation (2.32).

7. Termination Criteria

The termination of the algorithm was determined by a set number of iterations or generations. The algorithm also checked on the convergence of the solution. If either convergence or the maximum number of iterations was reached, the algorithm was terminated.

3.3.1.1 Evolution Programming Parameters

The control parameters of the Evolution Programming algorithm are Population Size and number of iterations. Table 3-4 shows the parameter used in the Evolution Programming method.

Table 3-4: Evolution Programming Parameters.

Parameter	Value
Population Size	200
Number of iterations	100

3.4 Sizing using Hybrid Evolution Programming

The Hybrid Evolution programming algorithm used to obtain DGs and Capacitors' optimal sizes is shown in Figure 3.3. The algorithm is explained in the following steps:

1. Representation of solution

Each trial solution was represented by the vector $S_p^T = [P_{Li} \quad Q_{Li}]$ where P_{Li} and Q_{Li} is the total active and reactive power, respectively, fed through the node i .

2. Initialization

The values of V_s , R_{si} and X_{si} of equation (3.2) are constants. V_s was set to 1, whereas values of R_{si} and X_{si} were calculated. The initial population was initialized randomly using a random uniform number and limiting the value of each element of the individual to be between the upper and lower boundaries of each variable, as shown in equation (3.14).

3. Power Flow solution

Power flow was run to determine the values of injected active and reactive power at each bus. Also, the voltage at each bus was determined. The power flow method used was forward/backward sweep.

4. Fitness Calculation

The fitness was calculated from the objective function shown by equation (3.2) to determine the optimality of the candidate solution.

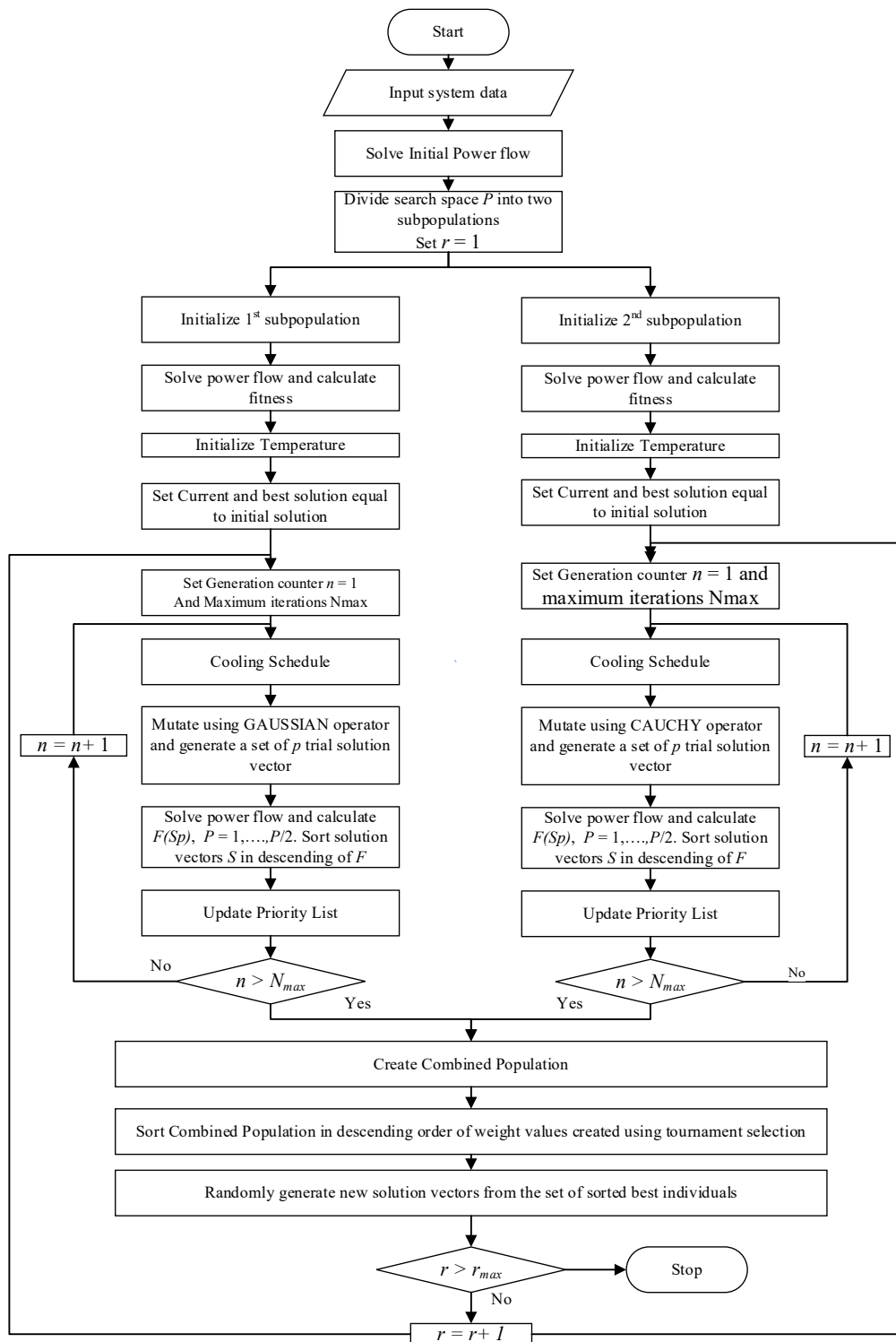


Figure 3.3: The HEP Algorithm used to obtain the sizes of DGs and Capacitors.

5. Cooling schedule

The initial temperature of each subpopulation was calculated using equation (3.18). This initial temperature was decreased using the simulated annealing cooling schedule in equation (3.19).

$$T_{0,m} = -(F_{\max,m} - F_{\min,m}) / \ln P_r \quad (3.18)$$

$$T_{r,m} = \lambda^{r-1} T_{0,m} \quad (3.19)$$

$T_{0,m}$ the initial temperature of the m th subpopulation.

$F_{\min,m}$ The objective value of the worst individual in the m th subpopulation.

$F_{\max,m}$ The objective value of the best individual in the m th subpopulation.

P_r -Probability of accepting the worst individual with respect to the best individual.

$T_{r,m}$ -annealing temperature of the m th subpopulation after the r^{th} reassignment

λ rate of cooling

r iteration counter of reassignment

6. Mutation

Two mutation operators were used to increase the diversity of the search. The two operators were the Gaussian operator and the Cauchy operator. The mutation operators were combined with the Cooling Schedule of Simulated Annealing. Each element of the offspring individual is calculated as shown in equation (3.20).

$$X'_{k,i} = X_{k,i} + \sigma_{k,i} * \xi_m \quad (3.20)$$

$$\sigma_{k,i} = T_{r,m} * a^{r-1} * (x_i^{\max} - x_i^{\min}) \quad (3.21)$$

where,

$X'_{k,i}$ - i th element of k th offspring individual

$X_{k,i}$ - i th element of k th parent individual

$\sigma_{k,i}$ - mutation step size for the i th element of the k th individual

ξ_m - mutation operator of the m th subpopulation, which includes

$C(0,1)$ and $N(0,1)$

$C(0,1)$ is Cauchy random number with parameter $t = 1$

$N(0,1)$ is a Gaussian random number with a mean 0 and standard deviation of 1.

a - a positive number slightly less than 1.

7. Tabu list

The Tabu list is used to keep a record of current best solutions. It has a finite length and stores the list of the current best solutions from the search process. The Tabu list is developed by replacing the worst solution in the list with a better solution during the search process. However, this Tabu restriction is overridden by the Acceptance Criterion of the Simulated Annealing if the Acceptance criterion is satisfied. The Acceptance Criterion is based on equation (3.21). The Tabu rule of replacing solutions in the finite Tabu List is overridden when a randomly generated variable in the interval $[0,1]$ is less than the probability acceptance criterion.

$$P_{k,m} = \frac{1}{\left(1 + \exp\left(-\Delta F / T_{r,m}\right)\right)} \quad (3.22)$$

where, $P_{k,m}$ is the probability acceptance criterion of the k th individual in the m th subpopulation, ΔF is the difference between the objective value of the k th offspring and the corresponding parent individual, and $T_{r,m}$ is the annealing temperature of the m th subpopulation after the r th reassignment.

8. Reassignment strategy

After the evolution of each subpopulation, a set of new offspring and parents was formed. To select a new population from the set of combined populations, a tournament selection method is used to select a new parent population for the next generation. This was done using equation (2.33).

9. Termination criteria

The termination of the algorithm was determined by a set number of iterations or the convergence of solutions. The algorithm terminates when there are no changes in the solutions in subsequent iterations or when the maximum number of iterations is reached.

3.4.1.1 HEP Parameters

Table 3-5 shows the parameter used in the Hybrid Evolution Programming method (Ongsakul & Dieu, 2016).

Table 3-5: HEP Parameters.

Parameter	Value
Population Size	200
Number of iterations	100
rate of cooling, λ	0.8
Probability of accepting the worst individual with respect to the best individual, P_r	0.3
a - a positive number slightly less than 1	0.95

CHAPTER FOUR

RESULTS, ANALYSIS AND DISCUSSION

4.1 Sizing using Evolution Programming

This algorithm was used to obtain optimal DGs and Capacitor sizes for IEEE-33 Bus radial distribution system. The number of locations for the DGs and Capacitor placement were determined by equation (3.11). From this equation, the number of locations for the placement was four. The four buses that had the lowest values of VSI were identified as the location points. These buses were 15, 16, 17, and 18. The algorithm for determining the sizes of the DGs and Capacitors was as shown in Figure 3.2. After running the algorithm, the optimal values of DG and capacitor obtained are shown in Table 4-1.

Table 4-1: Optimal sizes of DGs and Capacitors using EP algorithm.

Bus No.	Size of DG(kW)	Size of Capacitor (kVAr)
16	74.4	39.2
17	126	117.3
18	214	217.5

The total DG capacity obtained for placement within the distribution network using the EP placement algorithm was 494.7kW, whereas the total capacitor capacity was 451.6kVAr. The DG penetration was 13%.

The load flow data after placement of DGs and capacitors in the IEEE 33 bus radial network are shown in Table 4-2.

Table 4-2: Voltage and VSI after DG and Capacitor placement using EP algorithm.

Bus No.	Vbus	VSI	Bus No.	Vbus	VSI
1	1.0000	1.0000	18	0.9720	0.8889
2	0.9980	0.9999	19	0.9970	0.8926
3	0.9860	0.9907	20	0.9930	0.9879
4	0.9800	0.9449	21	0.9930	0.9723
5	0.9750	0.9221	22	0.9920	0.9723
6	0.9620	0.9020	23	0.9820	0.9683
7	0.9610	0.8564	24	0.9760	0.9295
8	0.9590	0.8529	25	0.9720	0.9073
9	0.9580	0.8458	26	0.9600	0.8926
10	0.9580	0.8423	27	0.9570	0.8493
11	0.9580	0.8423	28	0.9460	0.8377
12	0.9580	0.8423	29	0.9380	0.8003
13	0.9610	0.8422	30	0.9340	0.7740
14	0.9620	0.8529	31	0.9300	0.7609
15	0.9640	0.8564	32	0.9290	0.7480
16	0.9660	0.8636	33	0.9290	0.7448
17	0.9710	0.8706			

The network loading was increased by 25% before placement and after DG and capacitor placement to observe voltage and voltage stability index profile behavior. The voltage and VSI data for this increased loading are presented in Table 4-3.

**Table 4-3: Voltage and VSI data of IEEE-33 bus radial network at 125% loading
using DG and Capacitor values obtained using EP algorithm.**

Bus No.	No DG and Capacitor		DG and Capacitor installed		Bus No.	No DG and Capacitor		DG and Capacitor installed	
	Vbus	VSI	Vbus	VSI		Vbus	VSI	Vbus	VSI
1	1.0000	1.0000	1.0000	1.0000	18	0.8767	0.5929	0.9500	0.8111
2	0.9962	0.9989	0.9970	0.9999	19	0.9955	0.9219	0.9960	0.8145
3	0.9781	0.9793	0.9810	0.9857	20	0.9910	0.9821	0.9920	0.9839
4	0.9685	0.9127	0.9740	0.9256	21	0.9901	0.9646	0.9910	0.9684
5	0.9590	0.8776	0.9660	0.8995	22	0.9893	0.9611	0.9900	0.9645
6	0.9353	0.8402	0.9480	0.8678	23	0.9736	0.8924	0.9770	0.9604
7	0.9309	0.7648	0.9460	0.8075	24	0.9651	0.8980	0.9690	0.9104
8	0.9133	0.7482	0.9430	0.8008	25	0.9609	0.8676	0.9640	0.8815
9	0.9052	0.6951	0.9410	0.7907	26	0.9329	0.7714	0.9460	0.8635
10	0.8976	0.6708	0.9400	0.7840	27	0.9296	0.7570	0.9430	0.8008
11	0.8965	0.6491	0.9400	0.7807	28	0.9149	0.7450	0.9280	0.7890
12	0.8945	0.6458	0.9390	0.7807	29	0.9043	0.7000	0.9180	0.7408
13	0.8866	0.6400	0.9400	0.7774	30	0.8998	0.6688	0.9130	0.7100
14	0.8837	0.6179	0.9410	0.7807	31	0.8944	0.6553	0.9080	0.6946
15	0.8819	0.6098	0.9430	0.7840	32	0.8932	0.6399	0.9070	0.6797
16	0.8801	0.6048	0.9450	0.7907	33	0.8928	0.6365	0.9060	0.6768
17	0.8775	0.6000	0.9490	0.7973					

4.1.1 Analysis of Voltage Profile and Voltage Stability Indices obtained using EP algorithm

The main parameters used for the analysis of voltage stability were bus voltage values and voltage stability indices (VSIs). From the initial load flow, the minimum voltage for the IEEE 33-bus radial distribution network was 0.9036, while the minimum VSI was 0.6690. After placing the DGs and capacitors obtained using Evolution Programming, as shown in Table 4-1, the network's minimum voltage was 0.9290 while

the minimum VSI was 0.7480. This represents a 2.8% improvement on the minimum voltage and 11.8% improvement on the minimum VSI.

Table 4-4 shows the percentage improvement on the buses where the DGs and Capacitors were placed in the IEEE 33-bus radial distribution network. From these results, it was noted that the most significant improvement in voltage and VSI occurred at buses close to where the DGs and capacitors were installed. This can be attributed to the fact that when a DG and capacitor are installed at a bus, it alters current flow. The current flowing from the sending bus to the receiving bus decreases, and hence the voltage drop in the line is reduced. This, therefore, results in voltage improvement on the bus where the DG and capacitor are installed. This improvement was also realized on all buses in the radial distribution network. Also, the ranking order for VSI changed in that, the weakest buses before the placement of DGs and capacitors are no longer the lowest.

Table 4-4: Percentage improvement in voltage and VSI using EP values.

Bus No.		15	16	17	18
Voltage	Before Placement in p.u	0.908	0.906	0.904	0.9036
	After Placement in p.u	0.964	0.966	0.971	0.972
	Percentage Improvement	6.2	6.6	7.4	7.6
VSI	Before Placement	0.6829	0.6787	0.6746	0.669
	After Placement	0.8564	0.8636	0.8706	0.8889
	Percentage Improvement	25.4	27.2	29.1	32.9

The IEEE 33-bus loading was increased by 25% to check the effectiveness of placing the optimal sizes of DGs and Capacitors within the network when the load grows. It was observed that the minimum voltage before the placement with 125% loading was

0.8767 p.u while the minimum VSI was 0.5929. After the placement of the optimal sizes of DGs and capacitors and maintaining the loading at 125%, the minimum values of voltage and VSI were 0.906 p.u and 0.6768, respectively. This represents a percentage improvement of 3.34% on minimum network voltage and 14.2% on minimum VSI. The percentage improvement on VSI and Voltages at buses where DGs and Capacitors were installed are shown in Table 4-5.

Table 4-5: Voltage and VSI improvement for IEEE 33-bus for 125% loading using EP values.

Bus No.		15	16	17	18
Voltage	Before Placement in p.u	0.8819	0.8801	0.8775	0.8767
	After Placement in p.u	0.943	0.945	0.949	0.95
	Percentage Improvement	6.9	7.4	8.1	8.4
VSI	Before Placement	0.6098	0.6048	0.6	0.5929
	After Placement	0.784	0.7907	0.7973	0.8111
	Percentage Improvement	28.6	30.7	32.9	36.8

4.2 Sizing using Hybrid Evolution Programming Algorithm

The hybrid evolution programming (HEP) algorithm was used to place DGs and capacitors in the IEEE 33-bus network. The placement was done on bus No. 15, 16, 17, and 18. These buses had the lowest voltage stability indices. Table 4-6 shows the DGs and Capacitor sizes obtained using the HEP algorithm.

Table 4-6: DGs and Capacitors sizes obtained from HEP Algorithm.

Bus No.	Size of DG(kW)	Size of Capacitor (kVAr)
15	15.96	92.19
16	300.6	35.62
17	285.39	422.73
18	428.4	361.37

The total DG capacity obtained for placement within the distribution network using the Evolution Programming placement algorithm was 1030.35kW, whereas the total capacitor capacity was 911.91kVAr. This represented a DG penetration of 28%. The voltage and VSI values that resulted from placement of DG and capacitor sizes, shown in Table 4-6, in the IEEE-33 bus radial network are presented in Table 4-7.

Table 4-7: Voltage and VSI values after placement of DGs and Capacitors using HEP Algorithm.

						Bus		
Bus No.	Vbus	VSI	Bus No.	Vbus	VSI	No.	Vbus	VSI
1	1.0000	1.0000	12	0.9880	0.9451	23	0.9850	0.9722
2	0.9980	1.0000	13	0.9980	0.9518	24	0.9790	0.9409
3	0.9890	0.9912	14	1.0030	0.9917	25	0.9750	0.9185
4	0.9850	0.9566	15	1.0090	1.0118	26	0.9710	0.9037
5	0.9810	0.9412	16	1.0150	1.0361	27	0.9680	0.8889
6	0.9730	0.9254	17	1.0270	1.0598	28	0.9570	0.8769
7	0.9740	0.8963	18	1.0290	1.1124	29	0.9490	0.8382
8	0.9750	0.8999	19	0.9970	1.1211	30	0.9460	0.8110
9	0.9800	0.9034	20	0.9940	0.9879	31	0.9420	0.8007
10	0.9850	0.9221	21	0.9930	0.9762	32	0.9410	0.7874
11	0.9860	0.9413	22	0.9930	0.9723	33	0.9400	0.7841

The network loading was increased by 25% before placement and after DG and capacitor placement to observe voltage and voltage stability index profile behavior. The voltage and VSI data for this increased loading are presented in Table 4-8.

Table 4-8: Voltage and VSI values at 125% loading after placement of DG and capacitors using HEP algorithm.

Bus No.	Vbus	VSI	Bus No.	Vbus	VSI
1	1.0000	1.0000	18	1.0090	1.0282
2	0.9970	0.9999	19	0.9970	1.0365
3	0.9840	0.9864	20	0.9920	0.9878
4	0.9790	0.9372	21	0.9910	0.9684
5	0.9730	0.9183	22	0.9900	0.9645
6	0.9600	0.8946	23	0.9800	0.9604
7	0.9610	0.8493	24	0.9720	0.9217
8	0.9610	0.8529	25	0.9670	0.8924
9	0.9640	0.8527	26	0.9580	0.8743
10	0.9680	0.8634	27	0.9540	0.8422
11	0.9690	0.8780	28	0.9400	0.8265
12	0.9700	0.8816	29	0.9300	0.7799
13	0.9790	0.8845	30	0.9250	0.7479
14	0.9840	0.9184	31	0.9200	0.7319
15	0.9890	0.9373	32	0.9190	0.7164
16	0.9950	0.9564	33	0.9190	0.7133
17	1.0070	0.9788			

4.2.1 Analysis of Voltage Profile and Voltage Stability Indices obtained using HEP algorithm

The optimal values of DGs and Capacitors are indicated in Table 4-6. After these optimal sizes of DGs and capacitors were placed in the IEEE 33-bus radial distribution system, the minimum voltage obtained was 0.9400 p.u, whereas the minimum VSI was

0.7841. This represents a 4% improvement on minimum voltage and 17.2% on minimum VSI. The percentage improvement on the voltage and VSI at buses where DGs and capacitors were installed is shown in Table 4-9.

Table 4-9: Percentage improvement in voltage and VSI using HEP values.

Bus No.		15	16	17	18
Voltage	Before Placement in p.u	0.908	0.906	0.904	0.9036
	After Placement in p.u	1.009	1.015	1.027	1.029
	Percentage Improvement	11.1	12.0	13.6	13.9
VSI	Before Placement	0.6829	0.6787	0.6746	0.669
	After Placement	1.0118	1.0361	1.0598	1.1124
	Percentage Improvement	48.2	52.7	57.1	66.3

It was also observed that there was no considerable change of voltage levels at buses close to the source substation after the placement of DG and capacitors. At bus 19 of the IEEE 33 bus radial distribution network, the voltage value change after DG and capacitor placement is 0.0015pu. This represents the smallest voltage change in the network. Bus 19 is connected directly to bus two, which is very close to the source.

The small change in the value of voltage in this bus can therefore be attributed to the fact that there is a minimal voltage drop between the source and bus 19 owing to the proximity of bus 19 to the source substation. Further, the DGs and capacitors are placed on the farthest end of the IEEE 33 bus's main lateral. Therefore, the DGs and capacitors would not significantly alter the power flow near the source bus, hence the little change in voltage profile near the source bus.

After increasing the loading level by 25% for the IEEE 33-bus network and applying DGs and capacitors' values obtained using the HEP algorithm, the minimum values of voltage and VSI obtained were 0.9190 and 0.7133, respectively. This represents a 4.82% improvement on minimum voltage and a 20.2% improvement on minimum VSI. The percentage improvement on VSI and Voltages at buses where DGs and Capacitors were installed are shown in Table 4-10.

Table 4-10: Voltage and VSI improvement for IEEE 33-bus with 125% loading using HEP values.

Bus No.		15	16	17	18
Voltage	Before Placement in p.u	0.8819	0.8801	0.8775	0.8767
	After Placement in p.u	0.989	0.995	1.007	1.009
	Percentage Improvement	12.1	13.1	14.8	15.1
VSI	Before Placement	0.6098	0.6048	0.6	0.5929
	After Placement	0.9373	0.9564	0.9788	1.0282
	Percentage Improvement	53.7	58.1	63.1	73.4

4.2.2 Comparison of sizing using Evolution Programming and Hybrid Evolution Programming algorithms.

Voltage profiles showing a comparison of voltages at all buses before and after DG and Capacitor placement were plotted for 100% loading level and 125% loading level. Also, a comparison was made on voltage values at the buses where DGs and Capacitors were installed since they represented the highest voltage improvement in the entire radial distribution network.

Figure 4.1 and Figure 4.2 show the Voltage and VSI profiles, respectively, at all buses of the IEEE-33 bus radial distribution network before installing DGs and Capacitors after installing DGs and Capacitors using values obtained from the Evolution Programming algorithm, and after the installation of the DGs and Capacitors using values obtained using Hybrid Evolution Programming algorithm. From the Figure 4.2, the VSI goes slightly above one. This can be attributed to the voltage at the buses going beyond one p.u. The VSI is a function of the voltage and therefore if the voltage exceeds one, VSI increases beyond one.

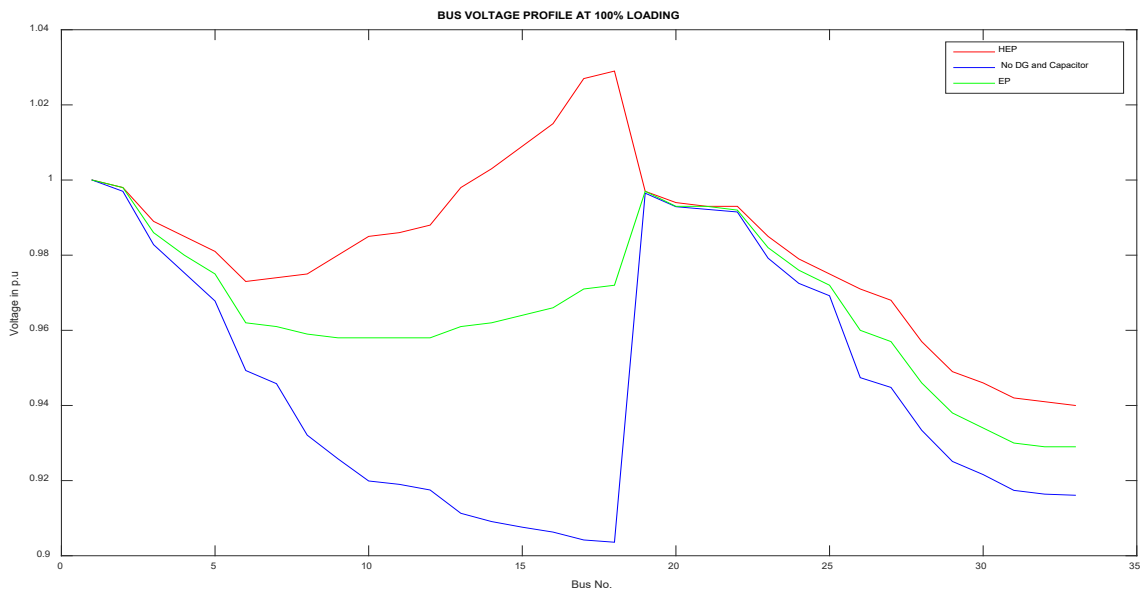


Figure 4.1: Voltage profile comparison for IEEE-33 Bus radial distribution network before and after DGs and Capacitors placement.

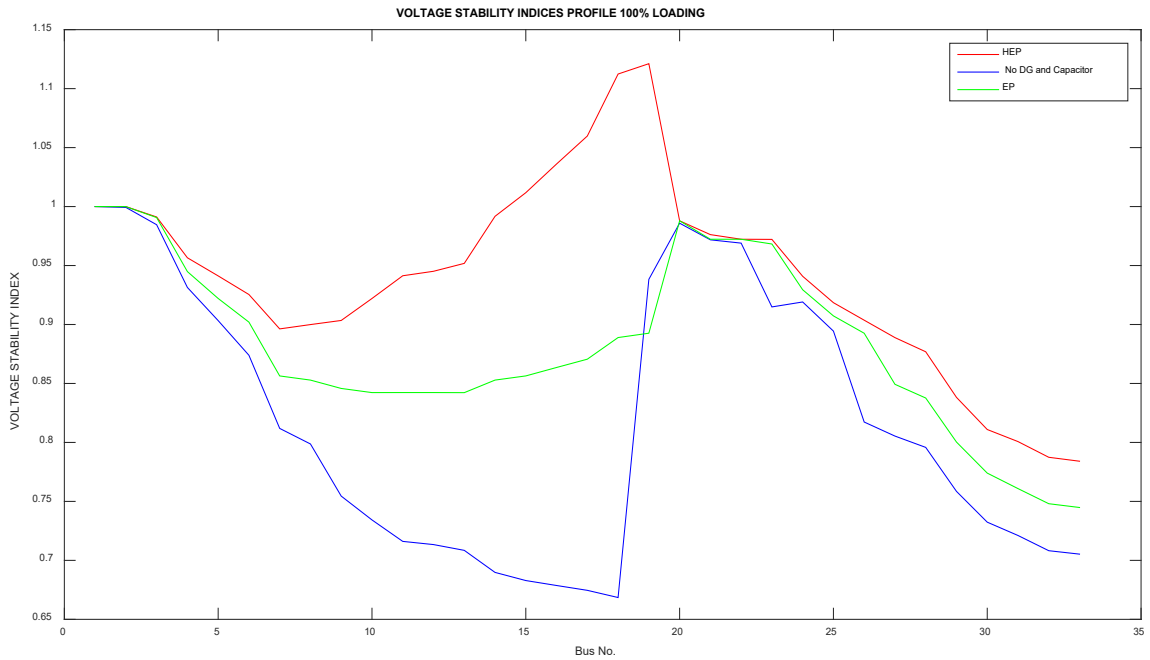


Figure 4.2: VSI comparison for IEEE-33 Bus radial distribution network before and after DGs and capacitors placement.

Figure 4.3 and Figure 4.4 show a comparison of voltage magnitude and VSI values, respectively, at buses 15 to bus 18, where the DGs and capacitors were placed. These buses had the most significant improvement in voltage stability. The comparison shows that the DG and Capacitor values obtained using HEP method gave the best results for voltage magnitude and VSI.

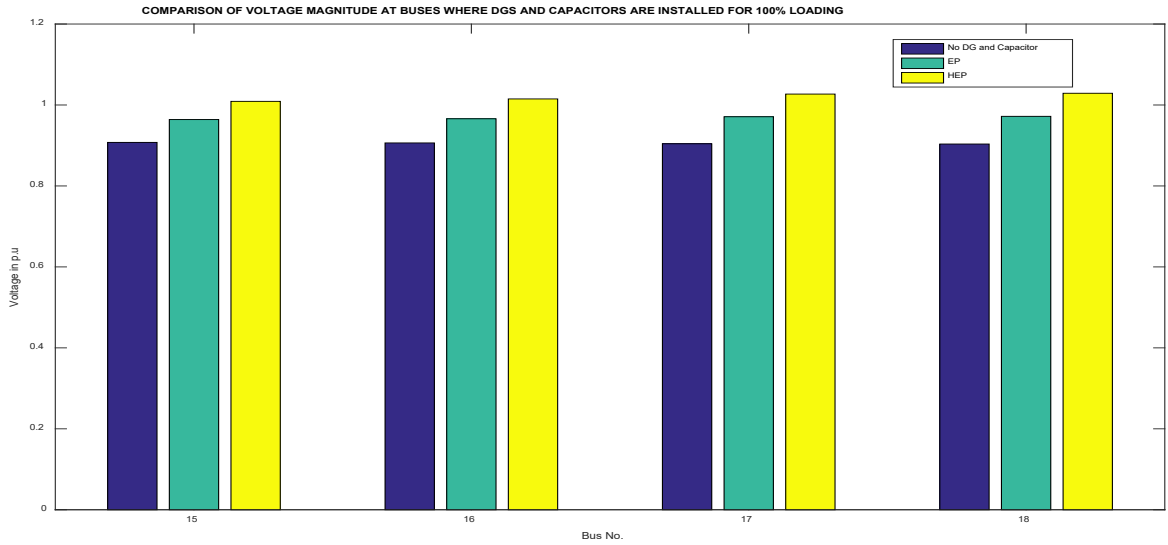


Figure 4.3: A comparison of voltage magnitude before and after DGs and Capacitors were installed for IEEE 33 Bus with 100% loading.

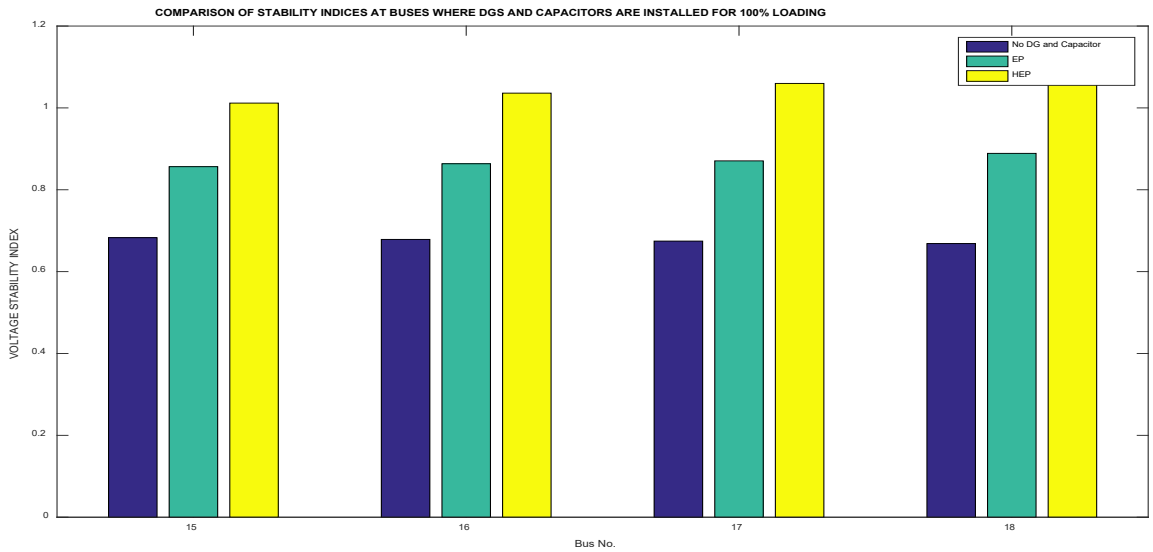


Figure 4.4: A comparison of VSI at buses before and after DGs and Capacitors were installed for IEEE 33 Bus with 100% loading.

The IEEE-33 bus radial network loading was increased by 25% to check the behavior of the network when load grows over time. The results of the voltage magnitudes and VSI at all buses were as shown in Figure 4.5 and Figure 4.6, respectively. Also, a comparison of voltage magnitudes and VSI of buses 15 to 18 is shown in Figure 4.7 and Figure 4.8, respectively. These buses represented the buses with the most significant improvement in voltage stability.

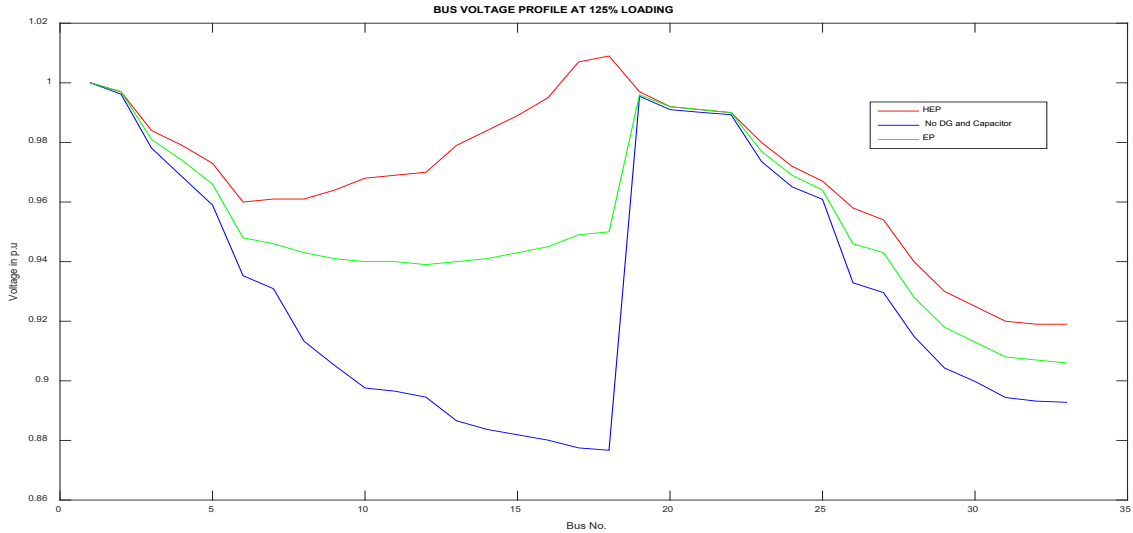


Figure 4.5: Comparison of voltage magnitude before and after DGs and Capacitors were installed for IEEE 33 Bus with 125% loading.

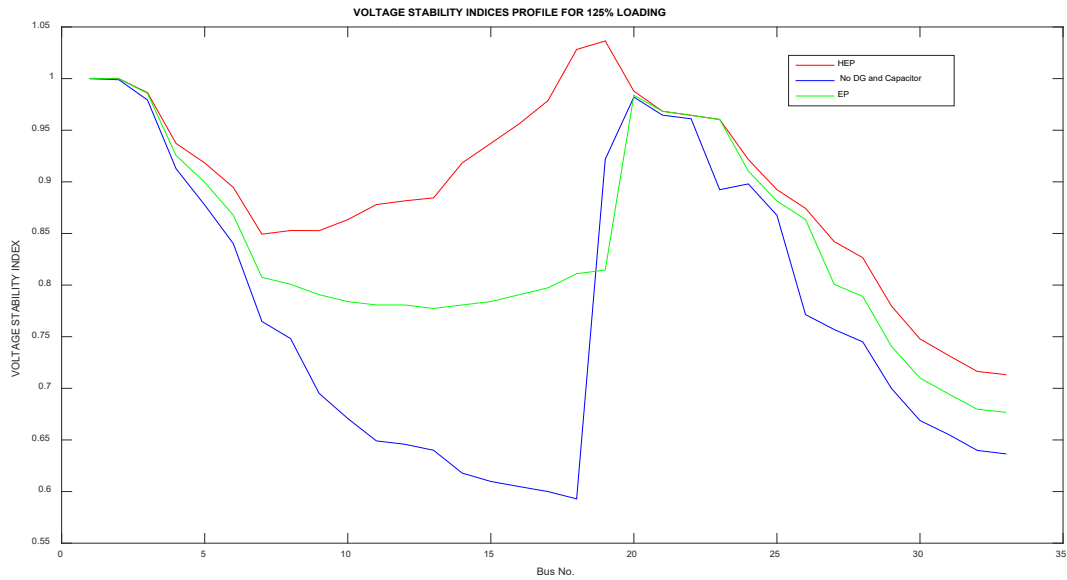


Figure 4.6: Comparison of VSI before and after DGs and Capacitors were installed for IEEE 33 Bus with 125% loading.

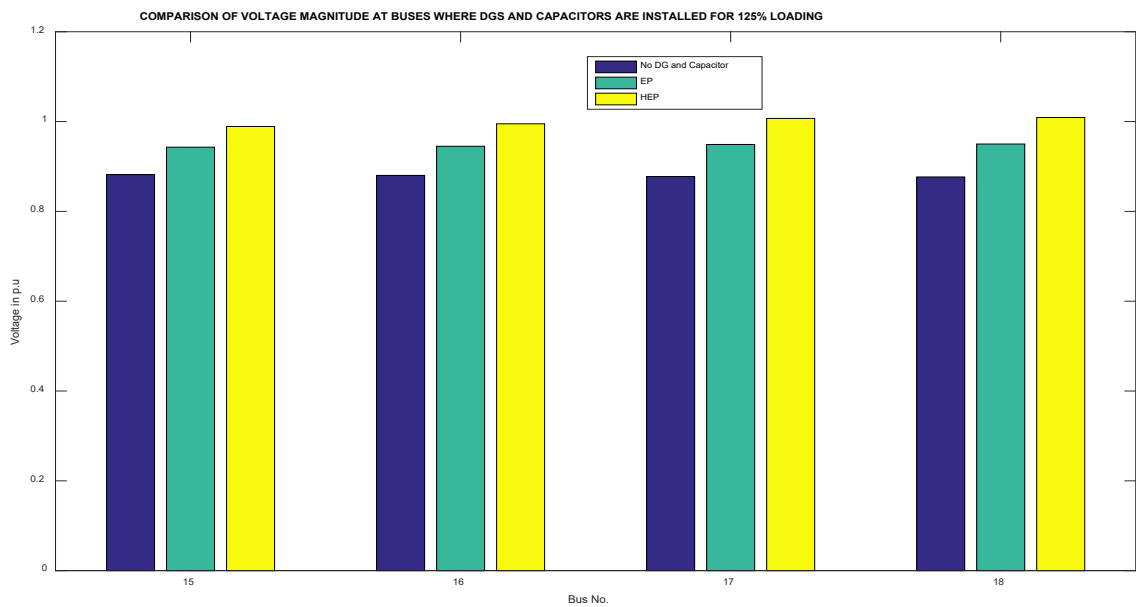


Figure 4.7: Comparison of voltage magnitude before and after DGs and Capacitors were installed for IEEE 33 Bus with 125% loading.

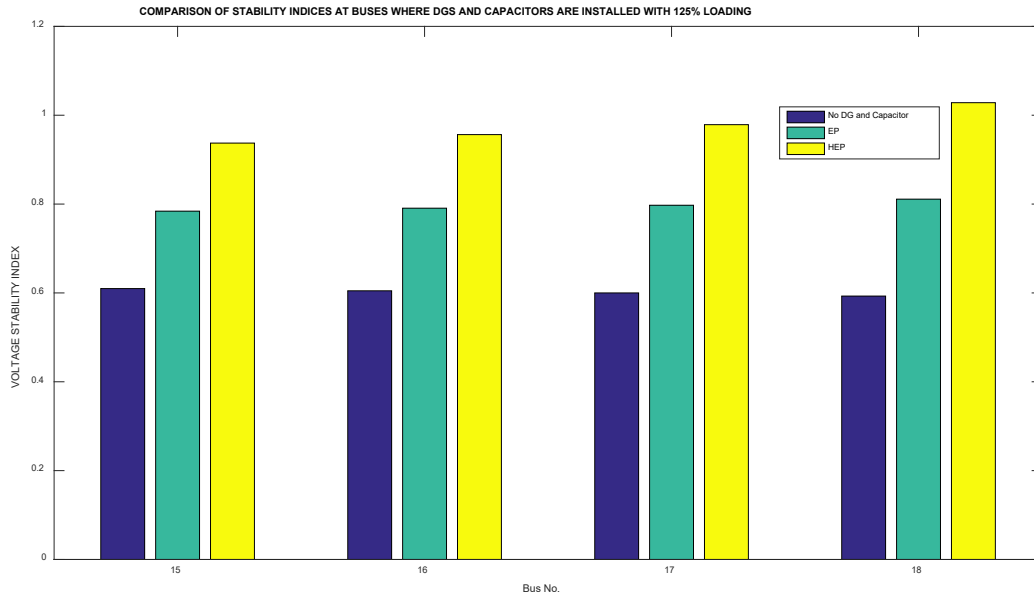


Figure 4.8: Comparison of VSI before and after DGs and Capacitors were installed for IEEE 33 Bus with 125% loading.

4.2.3 Analysis of comparison of EP and HEP

From the voltage comparison in Figure 4.1 the minimum voltage after placement with EP was 0.9290 p.u. at bus 31 which corresponded to a VSI of 0.7480 as shown in Figure 4.2. Increasing the load by 25% resulted in a minimum voltage of 0.906 p.u. at bus 33, as shown in Figure 4.5 which corresponding to a VSI of 0.6768 as shown in Figure 4.6. When HEP was used, the minimum voltage was 0.9400 as shown in Figure 4.1 which corresponds to a VSI of 0.7841, as shown in Figure 4.2. Increasing the load by 25% resulted in a minimum voltage of 0.919 p.u. at bus 33, as shown in Figure 4.5 which corresponding to a VSI of 0.7133 as shown in Figure 4.6. From this comparison, the HEP algorithm gave better results when compared to the EP algorithm. A comparison of

voltage and VSI values at the locations of DG and Capacitor placement, as shown in Figure 4.3, Figure 4.4, Figure 4.7, and Figure 4.8, reinforces this finding.

4.3 Placement results of IEEE-69 Bus Radial Distribution network

The Hybrid Evolution programming algorithm was used to place the DGs and Capacitors in the IEEE-69 Bus radial distribution network to determine its applicability on a larger radial network. To obtain the number of locations, equation (3.11) was used. The calculation resulted to four locations. Therefore, the DGs and Capacitors placement was done in buses 62, 63, 64, and 65. These buses had the lowest voltage stability indices. The optimal sizes of DGs and Capacitors obtained using HEP were as shown in Table 4-11.

Table 4-11: Optimal DGs and Capacitors sizes obtained using HEP.

Bus No.	Size of DG(kW)	Size of Capacitor (kVAr)
62	475.36	324.98
63	200.12	374.32
64	67.1	27
65	42.12	73.68

The total DG capacity obtained for placement within the distribution network using the HEP placement algorithm was 784.7kW, whereas the total capacitor capacity was 799.98kVAr. This represented a DG penetration of 21%. The values of voltage and VSI obtained after placement of the DGs and Capacitors in the IEEE-69 bus network are shown in Table 4-12.

The IEEE 69 bus network loading was increased by 25% before placement and after DG and capacitor placement to observe voltage and voltage stability index profile. The load demand of a distribution system is typically expected to grow over time, hence the 25% increase to account for this load growth. The voltage and VSI data for this increased loading is presented in Table 4-13.

Table 4-12: Voltage and VSI values after DGs and Capacitors placement.

Bus No.	Vbus	VSI	Bus No.	Vbus	VSI	Bus No.	Vbus	VSI	Bus No.	Vbus	VSI
1	1.0000	1.0000	19	0.9570	0.8388	37	1.0000	1.0000	55	0.9770	0.9111
2	1.0000	1.0000	20	0.9570	0.8388	38	0.9990	0.9960	56	0.9750	0.9028
3	1.0000	1.0000	21	0.9560	0.8353	39	0.9990	0.9960	57	0.9630	0.8598
4	1.0000	1.0000	22	0.9560	0.8353	40	0.9990	0.9960	58	0.9570	0.8388
5	0.9990	0.9957	23	0.9560	0.8353	41	0.9980	0.9920	59	0.9540	0.8283
6	0.9920	0.9681	24	0.9560	0.8353	42	0.9980	0.9920	60	0.9520	0.8213
7	0.9850	0.9413	25	0.9550	0.8318	43	0.9980	0.9920	61	0.9480	0.8077
8	0.9830	0.9337	26	0.9550	0.8318	44	0.9980	0.9920	62	0.9490	0.8111
9	0.9830	0.9335	27	0.9550	0.8318	45	0.9980	0.9920	63	0.9500	0.8145
10	0.9760	0.9074	28	1.0000	1.0000	46	0.9980	0.9920	64	0.9490	0.8111
11	0.9750	0.9036	29	1.0000	1.0000	47	1.0000	1.0000	65	0.9490	0.8111
12	0.9710	0.8889	30	1.0000	1.0000	48	0.9980	0.9918	66	0.9750	0.9037
13	0.9670	0.8743	31	1.0000	1.0000	49	0.9930	0.9723	67	0.9750	0.9037
14	0.9630	0.8599	32	1.0000	1.0000	50	0.9920	0.9684	68	0.9710	0.8889
15	0.9590	0.8458	33	0.9990	0.9960	51	0.9830	0.9337	69	0.9710	0.8889
16	0.9590	0.8458	34	0.9990	0.9960	52	0.9830	0.9337			
17	0.9580	0.8423	35	0.9990	0.9960	53	0.9810	0.9261			
18	0.9580	0.8423	36	1.0000	1.0000	54	0.9790	0.9186			

Table 4-13: Voltage and VSI values of IEEE 69 bus system at 125% loading.

Bus No.	No DG and Capacitor		DG and Capacitor installed		Bus No.	No DG and Capacitor		DG and Capacitor installed	
	Vbus	VSI	Vbus	VSI		Vbus	VSI	Vbus	VSI
1	1.0000	1.0000	1.0000	1.0000	36	1.0000	0.9960	1.0000	0.9960
2	1.0000	1.0000	1.0000	1.0000	37	1.0000	1.0000	1.0000	1.0000
3	1.0000	1.0000	1.0000	1.0000	38	0.9990	1.0000	0.9990	1.0000
4	1.0000	1.0000	1.0000	1.0000	39	0.9990	0.9960	0.9990	0.9960
5	0.9980	1.0000	0.9990	1.0000	40	0.9990	0.9960	0.9990	0.9960
6	0.9830	0.9906	0.9890	0.9954	41	0.9980	0.9960	0.9980	0.9960
7	0.9660	0.9322	0.9790	0.9561	42	0.9980	0.9920	0.9980	0.9920
8	0.9620	0.8707	0.9760	0.9186	43	0.9980	0.9920	0.9980	0.9920
9	0.9600	0.8564	0.9750	0.9074	44	0.9980	0.9920	0.9980	0.9920
10	0.9520	0.8490	0.9670	0.9033	45	0.9970	0.9920	0.9970	0.9920
11	0.9500	0.8214	0.9650	0.8744	46	0.9970	0.9881	0.9970	0.9881
12	0.9450	0.8144	0.9600	0.8670	47	1.0000	0.9881	1.0000	0.9881
13	0.9400	0.7974	0.9550	0.8492	48	0.9980	1.0000	0.9980	1.0000
14	0.9350	0.7806	0.9500	0.8317	49	0.9910	0.9917	0.9910	0.9917
15	0.9300	0.7642	0.9450	0.8144	50	0.9900	0.9645	0.9900	0.9645
16	0.9290	0.7480	0.9440	0.7975	51	0.9620	0.9606	0.9760	0.9606
17	0.9270	0.7448	0.9430	0.7941	52	0.9620	0.8564	0.9760	0.9074
18	0.9270	0.7384	0.9430	0.7908	53	0.9550	0.8563	0.9720	0.9074
19	0.9260	0.7384	0.9420	0.7908	54	0.9500	0.8316	0.9700	0.8926
20	0.9260	0.7353	0.9420	0.7874	55	0.9420	0.8142	0.9660	0.8852
21	0.9250	0.7353	0.9410	0.7874	56	0.9340	0.7871	0.9620	0.8707
22	0.9250	0.7321	0.9410	0.7841	57	0.8930	0.7531	0.9420	0.8544
23	0.9250	0.7321	0.9410	0.7841	58	0.8730	0.6343	0.9320	0.7870
24	0.9250	0.7321	0.9400	0.7841	59	0.8660	0.5806	0.9280	0.7544
25	0.9240	0.7321	0.9400	0.7807	60	0.8570	0.5621	0.9240	0.7416
26	0.9240	0.7289	0.9400	0.7807	61	0.8440	0.5388	0.9180	0.7288
27	0.9240	0.7289	0.9400	0.7807	62	0.8430	0.5074	0.9190	0.7102
28	1.0000	0.7289	1.0000	0.7807	63	0.8420	0.5050	0.9190	0.7133
29	1.0000	1.0000	1.0000	1.0000	64	0.8390	0.5026	0.9180	0.7133
30	1.0000	1.0000	1.0000	1.0000	65	0.8380	0.4955	0.9180	0.7102
31	1.0000	1.0000	1.0000	1.0000	66	0.9500	0.4931	0.9650	0.7102
32	0.9990	1.0000	0.9990	1.0000	67	0.9500	0.8145	0.9650	0.8672
33	0.9990	0.9960	0.9990	0.9960	68	0.9440	0.8145	0.9590	0.8672
34	0.9990	0.9960	0.9990	0.9960	69	0.9440	0.7941	0.9590	0.8458
35	0.9990	0.9960	0.9990	0.9960					

4.3.1 Voltage and VSI Profiles for IEEE-69 Bus radial distribution system

The voltage and VSI profiles for IEEE-69 Bus radial distribution system were plotted before and after the installation of DGs and Capacitors. Figure 4.9 and Figure 4.10 shows the Voltage profile and VSI profiles, respectively, for 100% network loading.

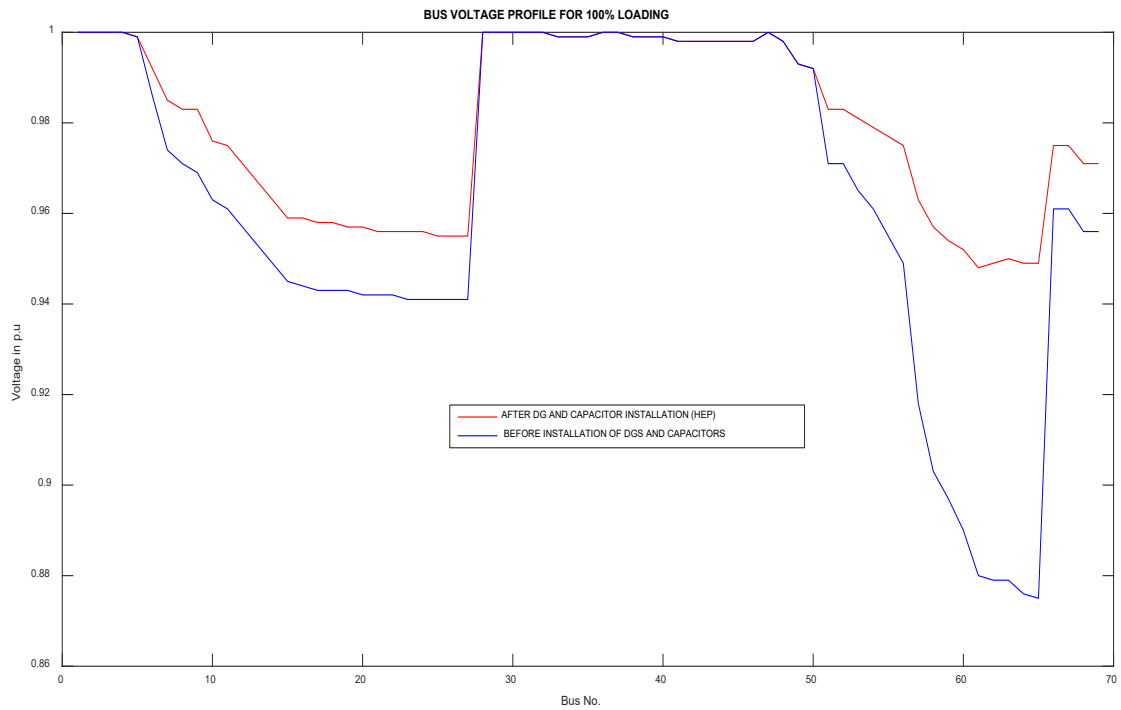


Figure 4.9: Voltage profiles for IEEE-69 Bus radial network before and after DGs and Capacitors placement.

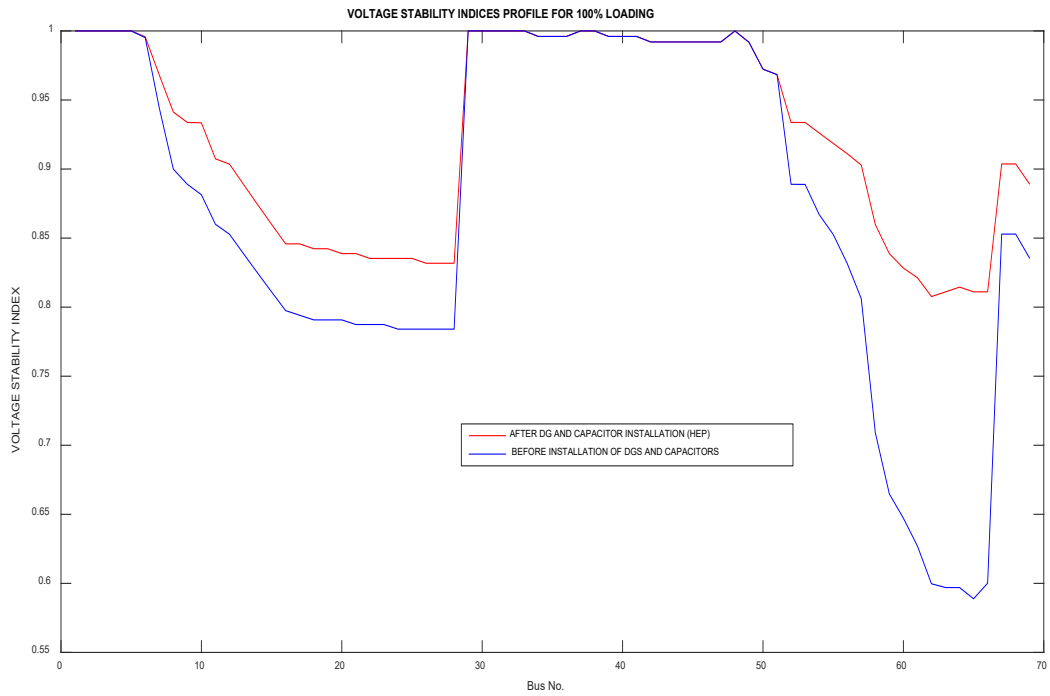


Figure 4.10: VSI for IEEE-69 Bus radial network before and after DGs and Capacitors placement.

A voltage and VSI comparison were made for buses where DGs and Capacitors were placed. These buses represent the most significant change in voltage stability. Figure 4.11 and Figure 4.12 show this comparison.

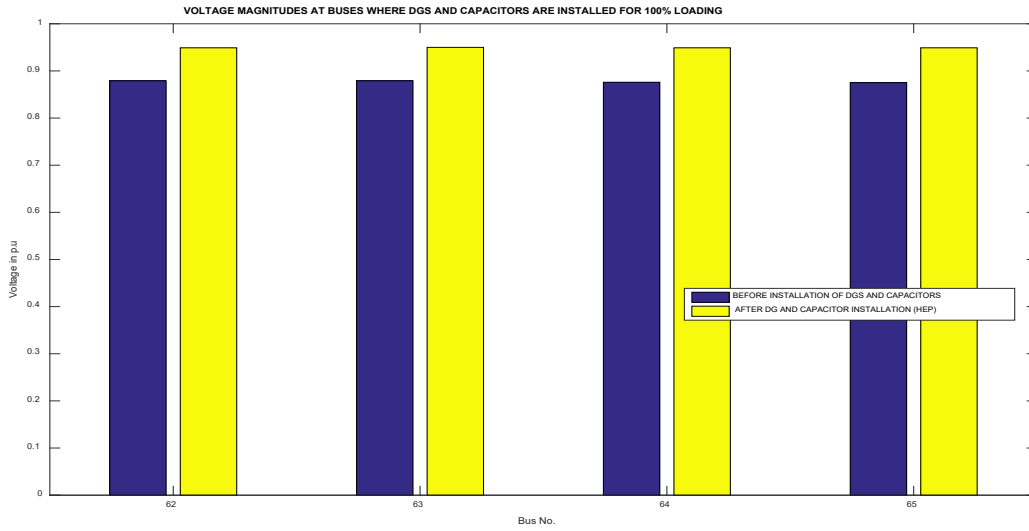


Figure 4.11: A comparison of voltage magnitudes at buses with DGs and Capacitors installed for 100% loading in the IEEE 69 bus network.

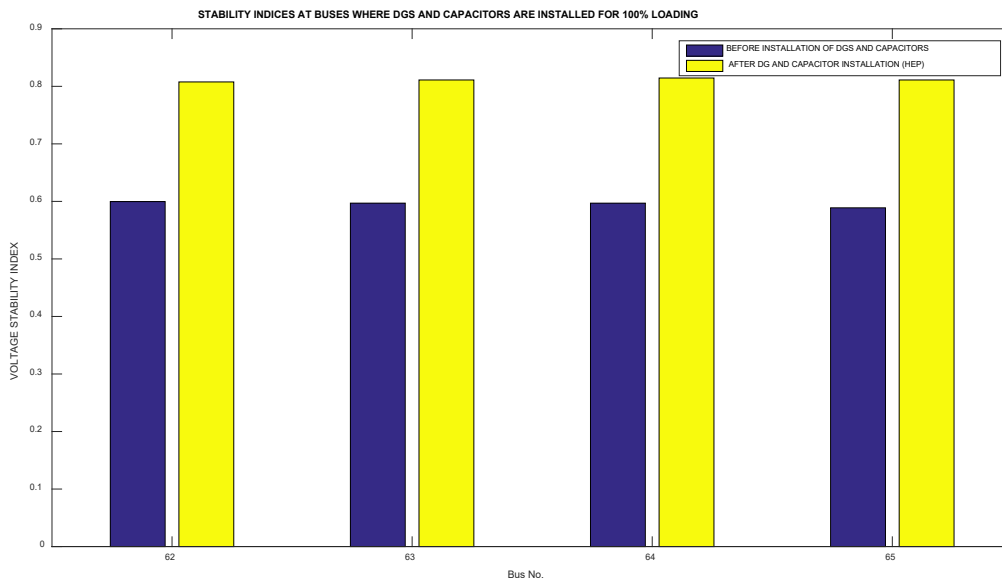


Figure 4.12: A comparison of VSI at buses with DGs and Capacitors installed for 100% loading in the IEEE-69 Bus network.

The loading level of the IEEE-69 bus radial network was increased by 25%. A comparison was made for this increase with and without DGs and capacitors placed in the network. Figure 4.12 and Figure 4.13 shows the voltage and VSI profiles, respectively, at all buses before and after DGs and Capacitors' placement. A comparison was also made for voltage and VSI at buses where DGs and capacitors were installed, as shown in Figure 4.15 and Figure 4.16, respectively.

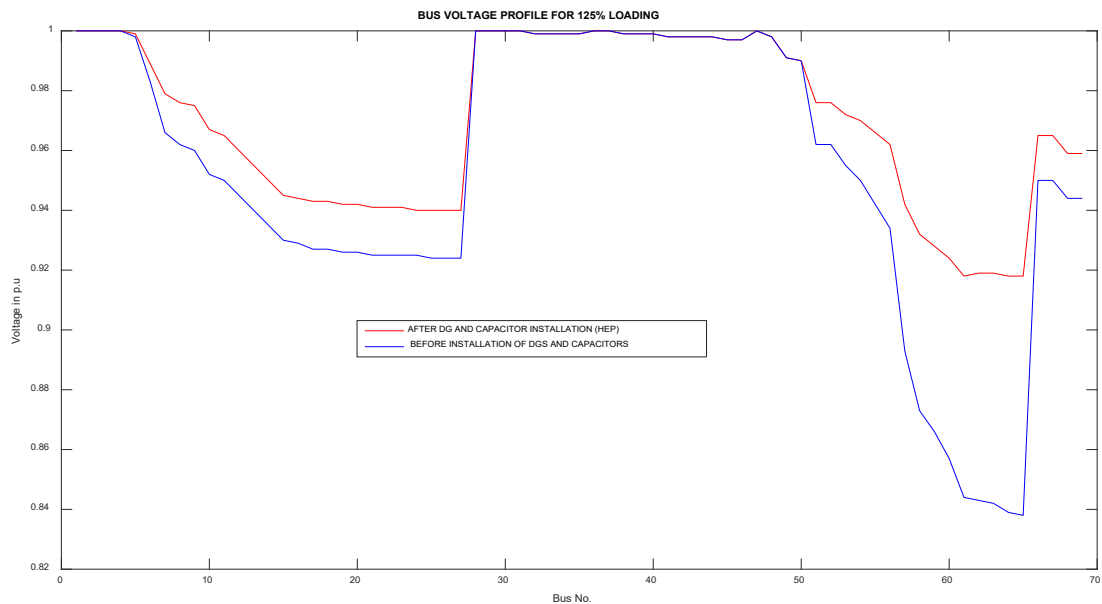


Figure 4.13: Voltage profiles of IEEE 69 Bus network with and without DGs and Capacitors for 125% loading.

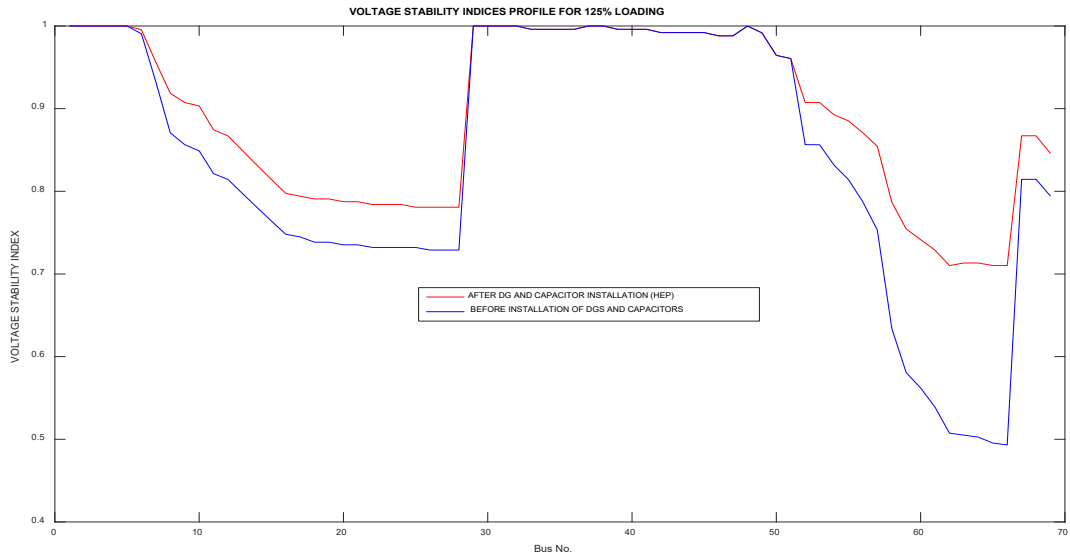


Figure 4.14: VSI profiles of IEEE 69 Bus network with and without DGs and Capacitors for 100% loading.

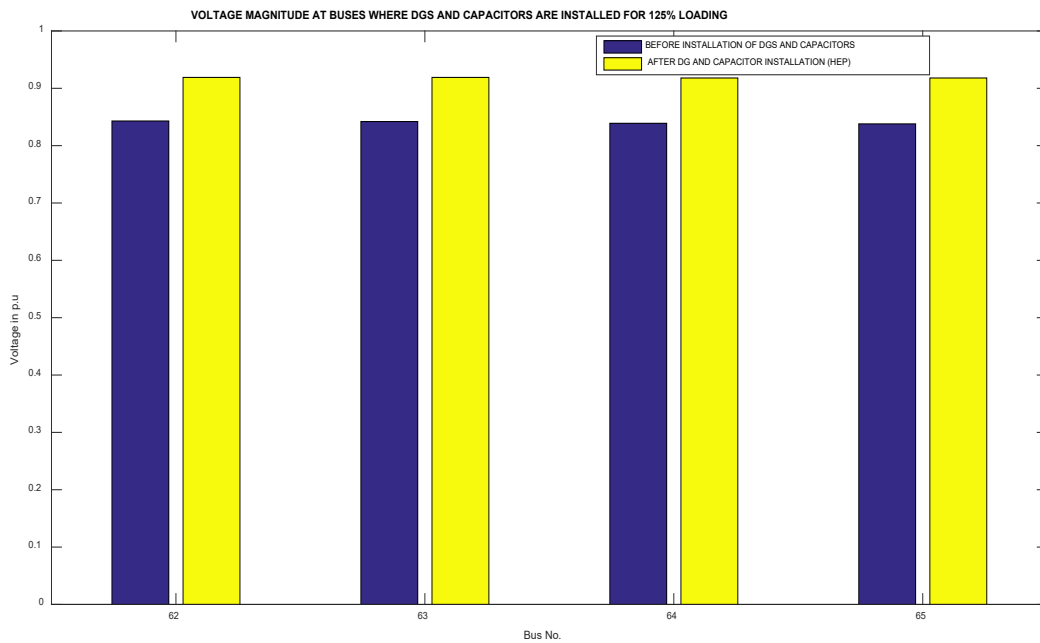


Figure 4.15: Voltage magnitude comparison of IEEE 69 Bus network with and without DGs and Capacitors for 125% loading at candidate buses.

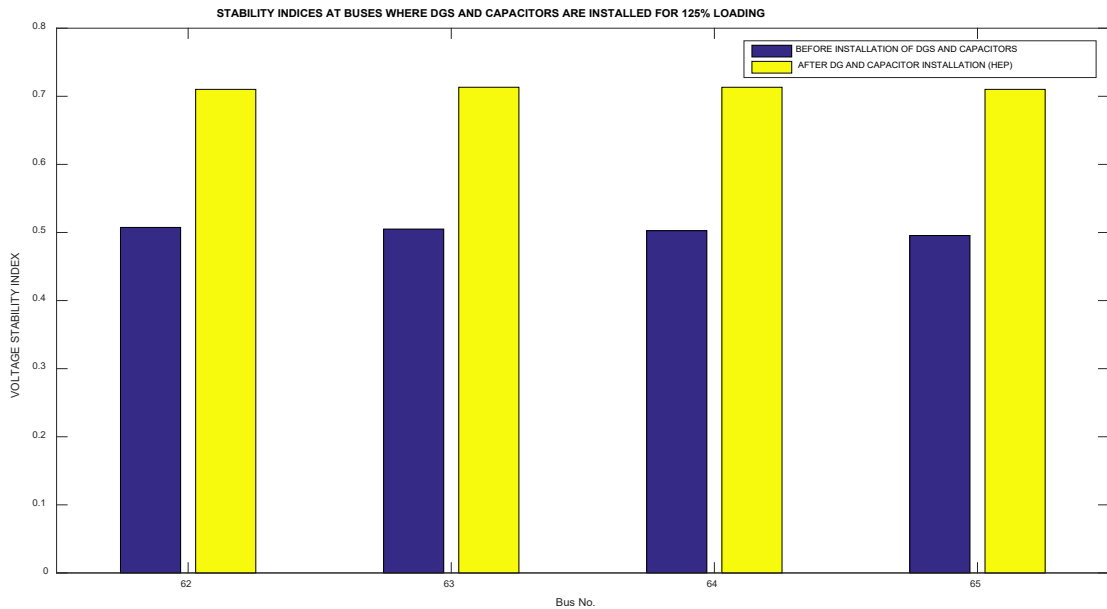


Figure 4.16: VSI comparison of IEEE 69 Bus network with and without DGs and Capacitors for 125% loading at candidate buses.

4.3.2 Analysis of Voltage Profile and Voltage Stability Indices for the IEEE-69 Bus

From the initial load flow, the minimum voltage for the IEEE 69-bus radial distribution network was 0.8750p.u while the minimum VSI was 0.5889. After placing the DGs and capacitors obtained using HEP, the network's minimum voltage was 0.9480p.u while the minimum VSI was 0.8077. This represents an 8.3% improvement on the minimum voltage and 37.2% improvement on the minimum VSI.

Table 4-14 shows the percentage improvement on the buses where the DGs and Capacitors were placed in the IEEE 69-bus radial distribution network. These buses had the most significant change in voltage magnitude and VSI values. From the comparison

in section 4.3.1, it is clear that the placement of DGs and Capacitors considerably improved the voltage profile for 100 % loading and when the load grows, as shown in Figure 4.11, Figure 4.12, Figure 4.15, and Figure 4.16. The improvement was most notable at the buses where the DGs and capacitors were placed. Also, the HEP method resulted in better voltage and VSI profiles for both 100% loading and 125% loading as shown in Figure 4.9, Figure 4.10, Figure 4.13, and Figure 4.14.

Table 4-14: Voltage and VSI improvement after DG and Capacitor placement in IEEE-69 Bus radial network at 100% loading.

Bus No.		62	63	64	65
Voltage	Before Placement in p.u	0.879	0.879	0.876	0.875
	After Placement in p.u	0.949	0.95	0.949	0.949
	Percentage Improvement	8.0	8.1	8.3	8.5
VSI	Before Placement	0.5997	0.597	0.5969	0.5889
	After Placement	0.8111	0.8145	0.8111	0.8111
	Percentage Improvement	35.3	36.4	35.9	37.7

From Figure 4.9, it was also observed that there was no considerable change of voltage levels at buses close to the source substation after the placement of DG and capacitors in the IEEE 69 bus radial distribution system. At bus 36 of the IEEE 69 bus radial distribution network, the voltage value change after DG and capacitor placement is 0.0 p.u. Bus 36 is connected directly to bus two, which is very close to the source. Therefore, there is a minimal voltage drop between the source and bus two due to bus two's proximity to the source substation. Further, the DGs and capacitors are placed between bus 62 and 65 which are far from the source bus and will not significantly alter

the power flow near the source bus, hence the little change in voltage profile near the source bus.

The IEEE 69-bus loading was increased by 25% to check the effectiveness of placing the optimal sizes of DGs and Capacitors within the network. It was observed that the minimum voltage before the placement with 125% loading was 0.8380 p.u while the minimum VSI was 0.4955. After the placement of the optimal sizes of DGs and capacitors and maintaining the loading at 125%, the minimum values of voltage and VSI were 0.9180 p.u and 0.7102, respectively. This represents a percentage improvement of 9.95% on minimum network voltage and 21.5% on minimum VSI. The percentage improvement on VSI and Voltages at buses where DGs and Capacitors were installed are shown in Table 4-15.

Table 4-15: Voltage and VSI improvement at buses where DGs and Capacitors have been installed in IEEE 69-bus loaded at 125%.

Bus No.		62	63	64	65
Voltage	Before Placement in p.u	0.843	0.842	0.839	0.838
	After Placement in p.u	0.919	0.919	0.918	0.918
	Percentage Improvement	9.0	9.1	9.4	9.5
VSI	Before Placement	0.5074	0.505	0.5026	0.4955
	After Placement	0.7102	0.7133	0.7133	0.7102
	Percentage Improvement	40.0	41.2	41.9	43.3

From the results obtained after DG and capacitor placement in the IEEE 69-bus radial distribution system, it is clear that the voltage profile and voltage stability of the

network were greatly enhanced. Therefore, the HEP algorithm developed is effective in DG and capacitor planning in radial distribution systems.

4.3.3 General observations

The total capacitor value obtained using EP was 451kVAr against 911.91kVAr when using HEP. It was observed that the minimum voltage obtained when the penetration of DG is 13% was 0.9290 p.u, whereas the minimum voltage obtained when the DG penetration is 28% is 0.9400p.u. From this, it can be concluded that the larger DG penetration gives a better voltage profile. However, the increase in the penetration of both the DG and capacitor, would certainly increase the installation cost.

The values of capacitors obtained were not in discrete sizes as found in practical applications. This would present a challenge since the capacitors would require to be custom made hence increasing the capacitors' cost. It was also observed that the Hybrid Evolution Programming method took on average ten minutes to converge as compared to Evolution Programming, which took on average five minutes to converge.

However, the results obtained when using Hybrid Evolution Programming were consistent on successive runs compared to Evolution Programming, which changed upon each subsequent run. This can be attributed to the fact that Evolution Programming presented different local optima results while those from Hybrid Evolution Programming were from the global optimum. Therefore, it can be concluded that the additional parameters from Simulated Annealing and Tabu Search algorithms ensure consistent results over subsequent program runs.

4.3.4 Analysis of Performance of Hybrid Evolution Programming as a method of Placement

The performance of the Hybrid Evolution Programming as a method for placement of DG and capacitors in radial distribution networks was compared with the results of intersect mutation differential evolution (IMDE) (Khodabakhshian & Andishgar, 2016), analytical method of loss sensitivity factors (LSF) (Mohan. & Aravindhbabu., 2010; Muthukumar & Jayalalitha, 2016) and Genetic Algorithm (GA) in (Moradi & Abedinie, 2010). IMDE is an un-hybridized form of Evolution Programming whereas LSF is an analytical method. GA, on the other hand, is a widely used heuristic method in DGs and Capacitor planning.

These methods were also used to solve the DGs and capacitors planning and therefore offered a good basis for validation of HEP as a placement method. The parameter used for comparison is the minimum voltage in the network after DG and Capacitor placement. The results of this comparison are shown in Table 4-16.

Table 4-16: Comparison of minimum voltage values using various algorithms.

	Methods used in Analysis of IEEE-33Bus			Method Used in Analysis of IEEE-69 Bus		
	HEP	IMDE(Khodabakhshian & Andishgar, 2016)	LSF(Muthukumar & Jayalalitha, 2016)	HEP	LSF(Mohan. & Aravindhbabu., 2010)	GA(Moradi & Abedinie, 2010)
Minimum Voltage (p.u)	0.9400	0.9323	0.9398	0.9480	0.9110	0.9200

The minimum voltage values obtained by using Hybrid Evolution Programming as the method for DG and Capacitor placement were relatively higher than those of IMDE, LSF, and GA. Therefore, it can be concluded that HEP is an effective method for DG and Capacitor placement in distribution networks.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS.

5.1 Conclusion

In this work, an algorithm for placing DGs and capacitors in radial distribution networks was developed. The backward-forward sweep load flow method was used to calculate network parameters. An objective function based on the voltage stability index was successfully developed. Voltage stability indices were calculated for both IEEE 33-bus and IEEE 69-bus radial distribution networks. The minimum voltage for the IEEE 33-bus distribution network before DG and capacitor placement was obtained as 0.9036p.u. whereas the minimum VSI was 0.6690.

The objective function was solved using both Evolution Programming and the developed Hybrid evolution programming. The minimum voltage obtained after placing DGs and capacitors using Evolution Programming in the IEEE 33-bus radial distribution network was 0.9290p.u, whereas the minimum VSI was obtained as 0.7480. On the other hand, when the placement was done using the developed HEP method, the minimum voltage and VSI for the network were improved to 0.9400p.u and 0.7841, respectively. Therefore, the placement values obtained using the developed HEP gave better results of voltage profile and voltage stability of the radial distribution network.

The DG penetration obtained using EP in the IEEE 33 Bus system was 13%, whereas that obtained using HEP was 28%. The higher penetration resulted in better

values of voltage and voltage stability index. The higher penetration would, however, result in higher installation costs. Also, the HEP algorithm took a longer time to converge as compared to the EP algorithm. However, consistent results were obtained in subsequent runs when HEP was used compared to the results obtained when EP was run. This can be attributed to the EP algorithm presenting results from various local optima. This problem of the EP algorithm being trapped in local optima was eliminated using the HEP method, hence the consistency of the search results upon successive runs.

The HEP method was also used to place DGs and capacitors in the IEEE 69-bus radial distribution network. The minimum network voltage for the IEEE 69 bus network was improved from 0.8750p.u to 0.9480p.u while the minimum VSI was improved from 0.5889 to 0.8077. Therefore, the optimal placement of DGs and capacitors in radial distribution networks using the developed HEP method improves the system voltage profile and voltage stability of a radial distribution system. The higher voltage and VSI values obtained when VSI was obtained can be attributed to the higher DG penetration. A higher DG penetration, however, would result to higher installation costs of DG and Capacitors. Therefore, an optimization involving installation costs can be done to explore the cost factor of the DG and capacitor placement problem.

Lastly, a comparison was made on the HEP methods with other methods that solved the DG and capacitor placement problem. These methods included Loss Sensitivity Factors, Genetic Algorithm, and Intersect Mutation Differential Evolution. The loss sensitivity method is an analytical method that places only a single DG at a time in the

distribution network. Genetic Algorithm and Intersect Mutation Differential Evolution are similar to Evolution Programming in that they imitate the evolution process. The HEP method gave a better voltage profile when compared to these methods. Therefore, it was concluded that the HEP method is a useful tool in the DGs and Capacitor placement problem.

5.2 Recommendations

This research developed a method for the placement of DGs and capacitors in radial distribution networks. Only type one DGs were considered. Future research can determine Hybrid Evolution Programming's applicability to the placement of type II, type III, and type IV DGs in radial distribution systems. A multi-objective function that incorporates the cost of DG and capacitor placement, taking into account step sizes of capacitors, together with voltage stability, can be developed to test the HEP algorithm's applicability.

Also, algorithm parameters for HEP, such as memory usage and search speed, can be analyzed to gauge its applicability in other areas such as real-time applications. This work also looked at the optimal placement of DG and Capacitor at the same bus simultaneously. Future studies can be undertaken to place the DGs and capacitors on different buses of the distribution network.

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APPENDICES

Appendix I: IEEE 33-Bus Radial Distribution Network

Figure A.1 shows the configuration of the IEEE 33 Bus radial distribution system.

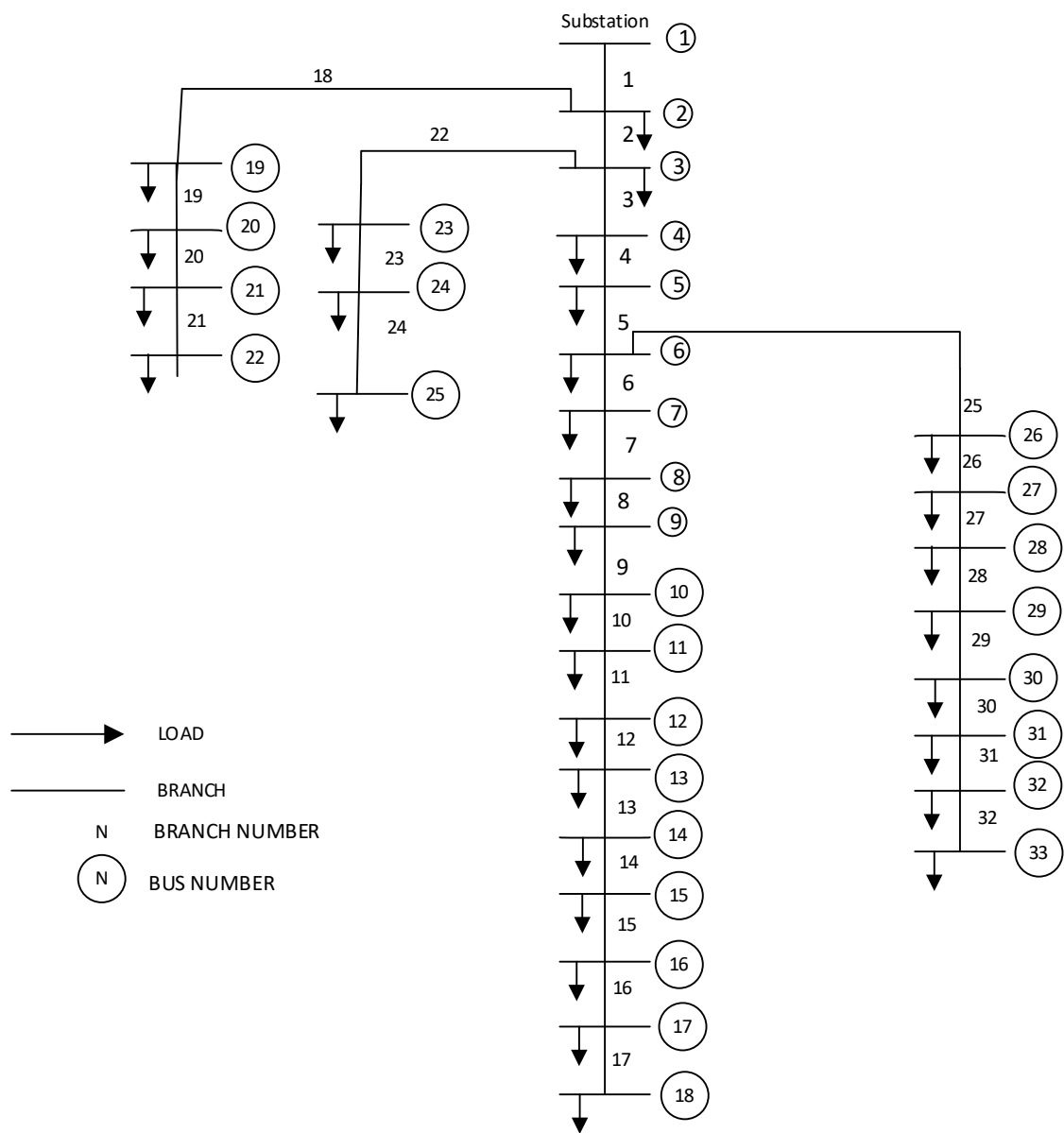


Figure A.1: IEEE 33-Bus radial distribution network.

Table A-1 shows the branch and bus data for the IEEE 33-bus radial distribution network.

Table A-1: IEEE 33-bus radial network parameters.

Sending Bus	Receiving Bus	R(Ohms)	X(Ohms)	load at receiving bus	
				P	Q
1	2	0.0922	0.0477	100	60
2	3	0.4930	0.2511	90	40
3	4	0.3660	0.1864	120	80
4	5	0.3811	0.1941	60	30
5	6	0.8190	0.7070	60	20
6	7	0.1872	0.6188	200	100
7	8	1.7114	1.2351	200	100
8	9	1.0300	0.7400	60	20
9	10	1.0400	0.7400	60	20
10	11	0.1966	0.0650	45	30
11	12	0.3744	0.1238	60	35
12	13	1.4680	1.1550	60	35
13	14	0.5416	0.7129	120	80
14	15	0.5910	0.5260	60	10
15	16	0.7463	0.5450	60	20
16	17	1.2890	1.7210	60	20
17	18	0.7320	0.5740	90	40
2	19	0.1640	0.1565	90	40
19	20	1.5042	1.3554	90	40
20	21	0.4095	0.4784	90	40
21	22	0.7089	0.9373	90	40
3	23	0.4512	0.3083	90	50
23	24	0.8980	0.7091	420	200
24	25	0.8960	0.7011	420	200
6	26	0.2030	0.1034	60	25
26	27	0.2842	0.1447	60	25
27	28	1.0590	0.9337	60	20
28	29	0.8042	0.7006	120	70
29	30	0.5075	0.2585	200	600
30	31	0.9744	0.9630	150	70
31	32	0.3105	0.3619	210	100
32	33	0.3410	0.5302	60	40

System voltage is 12.66 kV

Appendix II: IEEE 69-Bus Radial Distribution Network

Figure A.2 shows the configuration of the IEEE 69 Bus radial distribution system.

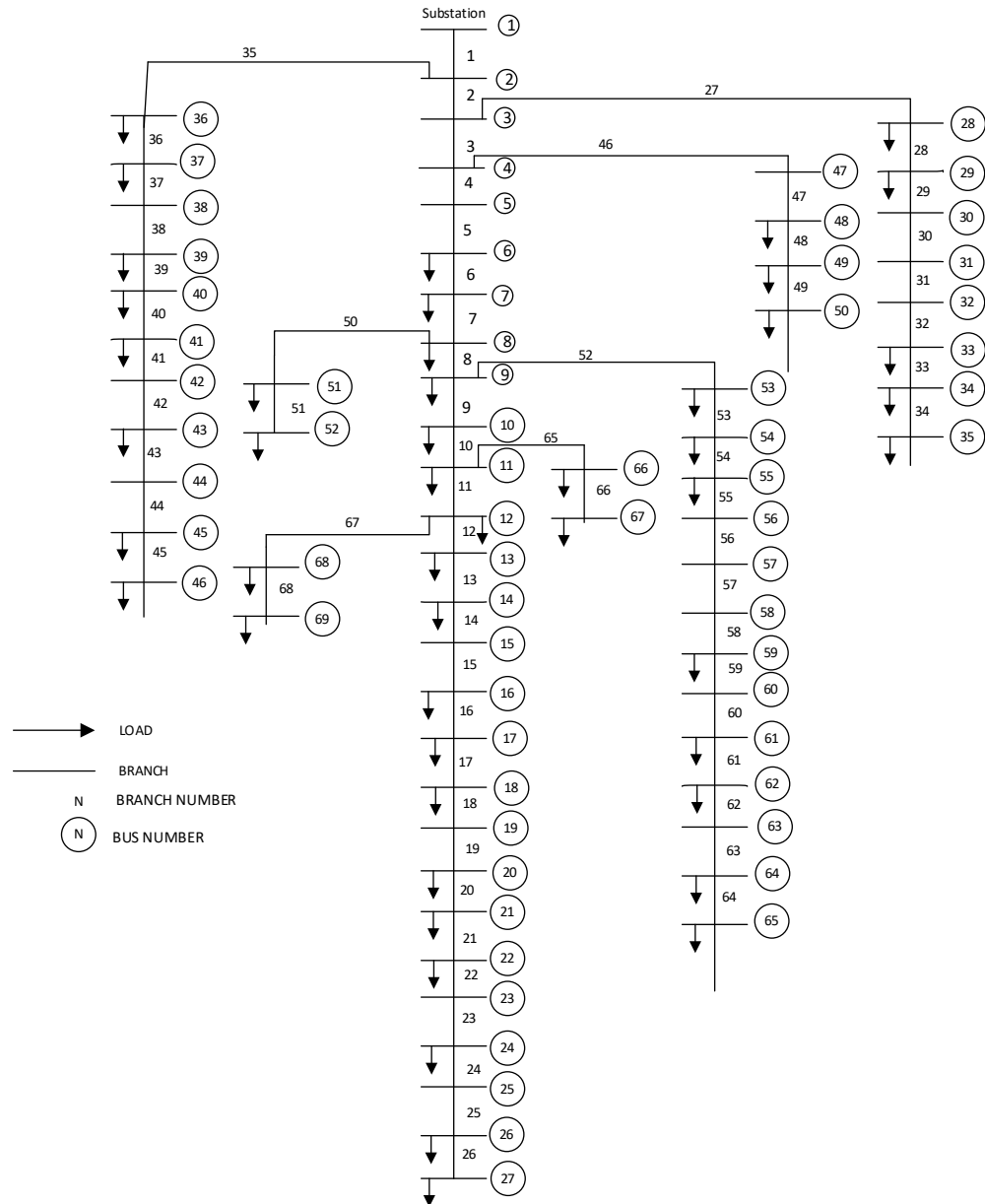


Figure A.2: IEEE 69-bus single line diagram

Table A-1 shows the branch and bus data for the IEEE 69-bus radial distribution network.

Table A-2: IEEE 69-bus system data.

Load at Receiving Bus						Load at Receiving Bus					
Sending Bus	Receiving Bus	R(ohms)	X(ohms)	P (kW)	Q(kVAr)	Sending Bus	Receiving Bus	R(ohms)	X(ohms)	P (kW)	Q(kVAr)
1	2	0.0005	0.0012	0	0	3	36	0.0044	0.0108	26	18.55
2	3	0.0005	0.0012	0	0	36	37	0.064	0.1565	26	18.55
3	4	0.0015	0.0036	0	0	37	38	0.1053	0.123	0	0
4	5	0.0251	0.0294	0	0	38	39	0.0304	0.0355	24	17
5	6	0.366	0.1864	2.6	2.2	39	40	0.0018	0.0021	24	17
6	7	0.3811	0.1941	40.4	30	40	41	0.7283	0.8509	1.2	1
7	8	0.0922	0.047	75	54	41	42	0.31	0.3623	0	0
8	9	0.0493	0.0251	30	22	42	43	0.041	0.0478	6	4.3
9	10	0.819	0.2707	28	19	43	44	0.0092	0.0116	0	0
10	11	0.1872	0.0619	145	104	44	45	0.1089	0.1373	39.22	26.3
11	12	0.7114	0.2351	145	104	45	46	0.0009	0.0012	39.22	26.3
12	13	1.03	0.34	8	5	4	47	0.0034	0.0084	0	0
13	14	1.044	0.345	8	5.5	47	48	0.0851	0.2083	79	56.4
14	15	1.058	0.3496	0	0	48	49	0.2898	0.7091	384.7	274.5
15	16	0.1966	0.065	45.5	30	49	50	0.0822	0.2011	384.7	274.5
16	17	0.3744	0.1238	60	35	8	51	0.0928	0.0473	40.5	28.3
17	18	0.0047	0.0016	60	35	51	52	0.3319	0.1114	3.6	2.7
18	19	0.3276	0.1083	0	0	9	53	0.174	0.0886	4.35	3.5
19	20	0.2106	0.069	1	0.6	53	54	0.203	0.1034	26.4	19
20	21	0.3416	0.1129	114	81	54	55	0.2842	0.1447	24	17.2
21	22	0.014	0.0046	5	3.5	55	56	0.2813	0.1433	0	0
22	23	0.1591	0.0526	0	0	56	57	1.59	0.5337	0	0
23	24	0.3463	0.1145	28	20	57	58	0.7837	0.263	0	0
24	25	0.7488	0.2475	0	0	58	59	0.3042	0.1006	100	72
25	26	0.3089	0.1021	14	10	59	60	0.3861	0.1172	0	0
26	27	0.1732	0.0572	14	10	60	61	0.5075	0.2585	1244	888
3	28	0.0044	0.0108	26	18.6	61	62	0.0974	0.0496	32	23
28	29	0.064	0.1565	26	18.6	62	63	0.145	0.0738	0	0
29	30	0.3978	0.1315	0	0	63	64	0.7105	0.3619	227	162
30	31	0.0702	0.0232	0	0	64	65	1.041	0.5302	59	42
31	32	0.351	0.116	0	0	11	66	0.2012	0.0611	18	13
32	33	0.839	0.2816	14	10	66	67	0.0047	0.0014	18	13
33	34	1.708	0.5646	9.5	14	12	68	0.7394	0.2444	28	20
34	35	1.474	0.4873	6	4	68	69	0.0047	0.0016	28	20

Appendix III: Conference and Journal Papers Published

From this research, the following two conference papers and one journal paper were published.

Chege, S. N., Murage, D. K., & Kihato, P. K. (2019). Optimal Placement of Distributed Generation and Capacitors in Radial Distribution Networks Using Hybrid Evolution Programming Algorithm. *European Journal of Advances in Engineering and Technology*, 6(1), 19–31.

Chege, S. N., Murage, D. K., & Kihato, P. K. (2018a). A Review of Load Flow Methods in Analysis of Power Distribution Systems. *Proceedings of the Sustainable Research and Innovation Conference*, 59–62.

Chege, S. N., Murage, D. K., & Kihato, P. K. (2018b). Distribution Generation and Capacitor Placement in Distribution Systems. *Proceedings of the Sustainable Research and Innovation Conference*, 63–69.